VNIVERSITAT DE VALÈNCIA

Facultat d'Economia

Departament d'Economia Financera i Actuarial

Programa de Doctorado en Finanzas y Economía Cuantitativas

ESSAYS ON EUROPEAN NATURAL GAS MARKET

Dissertation presented by:

Beatriz Martínez Martínez

Supervised by:

Hipòlit Torró Enguix

Valencia, Diciembre 2017

A mi hija

Agradecimientos

En primer lugar, me gustaría agradecer a mi tutor, Hipòlit Torró, su incondicional apoyo, incansable dedicación e infinita paciencia. Quiero agradecerle todo lo que he aprendido a su lado, sus constantes ideas de mejora y su implicación. Sin su inestimable ayuda, esta tesis nunca se habría llevado a cabo. Ha sido un placer trabajar y aprender a su lado, es una gran persona y un gran profesional.

Agradezco el apoyo financiero recibido del proyecto de investigación ECO2013-40816-P. del Ministerio de Economía y Competitividad, y de la Cátedra de Finanzas Internacionales del Banco Santander de la Universidad de Valencia, especialmente a su responsable, Constantino José García Martín. También la financiación recibida durante la beca F.P.U. de Formación del Profesorado Universitario del Ministerio de Educación, así como la beca de movilidad dentro de este programa, que me permitió realizar una estancia de investigación en el DIW Berlin (the German Institute for Economic Research).

Me gustaría agradecer a los profesores y responsables del Doctorado en Banca y Finanzas Cuantitativas, tanto a los de Valencia como a los de Madrid, Bilbao y Castilla la Mancha, por todo lo aprendido pero también por su comprensión y apoyo cuando la salud me jugó una mala pasada. A sus responsables, Francisco Climent y especialmente a Ángel Pardo, que como director, me ha guiado en la intrincada burocracia. También a mis compañeros y amigos, a los que codo con codo estuvieron ahí durante los dos cursos que duró el máster, Cristina y Óscar, Nerea y Vero. A los que precediéndome, me guiaron, Laura y Pilar. Y a los que llegaron después, Vicente, Chema y Fernando. Gracias a todos, porque todos y cada uno habéis hecho posible que llegue este momento.

Quiero dar las gracias a todos los revisores, tanto de la tesis (Lilian de Menezes, María Dolores Furió, Gregorio Serna, Julio Lucia, Ignacio Peña y María Mansanet) como de los correspondientes capítulos, que con sus comentarios y sugerencias, han mejorado sustancialmente la calidad de este trabajo.

Agradezco a mis compañeros y amigos del Departamento de Finanzas Empresariales todo el apoyo que me han brindado desde que me incorporé, por el buen ambiente de trabajo que se disfruta, sin olvidar a los compañeros y amigos de Economía Financiera y Actuarial, dónde esta tesis comenzó. Gracias por los sabios y experimentados consejos que recibo, que me ayudan a mejorar personal y profesionalmente.

Finalmente agradecer a mi familia todo su apoyo a lo largo de todos estos años, por el tiempo que les he robado, especialmente a mi hija, Sofía. A mí marido, José Andrés, que ha hecho todo mucho más fácil, encargándose de todo para que yo no me tuviera que me preocupar de nada. A mis padres, Ricar y Angelita, que desde bien pequeña me inculcaron el amor por aprender y superarme. A mi hermana, Paz, que siempre está ahí, pase lo que pase, para todo lo que necesite. A mis amigas y amigos de Sinarcas, que no entienden muy bien lo que hago, ni para qué sirve, pero siempre me han dado ánimos para continuar en los momentos de flaqueza. A mí familia política y a tíos y primos. A todos ellos les estoy infinitamente agradecida por haber estado ahí, especialmente en los momentos más duros, cuándo no veía el final del túnel.

Gracias a todos, a los mencionados y a los inconscientemente omitidos (ruego me disculpen), por el camino recorrido y por hacer posible la consecución de esta etapa, con sus altos y sus bajos, pero que sin duda me han hecho crecer, personal y profesionalmente.

Gracias.

Contents

Introduction

1. **Introduction**

The gradual liberalization of natural gas markets in Europe in the 1990s and 2000s signified a profound change in European energy markets. The reforms introduced have not only meant increasing competitiveness, but have also brought with them strong volatility instability, creating a need for instruments to manage and hedge price and volume risks. In this changing and dynamic context, it is crucial for market participants to adequately monitor risk and price signals in order to take appropriate decisions related to production, consumption, investment and risk management.

The main objectives of this doctoral thesis are the analysis and risk management of natural gas prices using futures contracts and the study of forward price formation in European natural gas markets, as well as its decomposition into expected price and risk premiums. Specifically, in chapter one, hedging strategies have been designed and analysed to cover natural gas risk price in three representative European natural gas markets. In chapter two, the behaviour of the risk premium in the British gas market and its relationship with risk variables have been characterized, comparing the conventional risk premium with the accrued risk premium obtained by rolling-over positions in the front contract. In chapter three, an extension of the analysis carried out in chapter one is applied to hedge the spark spread contract.

A common feature of price behaviour in energy markets is that changes in the spot price are partially predictable due to the influence of weather and strong seasonal demand. In chapter one a study is carried out on the existence of seasonality in the first and second moments of price returns. These predictable seasonal price movements are also incorporated to compute the unexpected spot price change, both in the hedging ratio computation and in the measurement of hedging effectiveness, applying the Ederington and Salas (2008) framework (E&S (2008)). In their paper, they adapt the standard minimum variance hedge ratio approach (Ederington, 1979) to the case where spot price changes are partially predictable. They propose using the basis (futures price minus the spot price) at the beginning of the hedge as the information variable to approximate the expected spot price change. They argue that if futures prices are unbiased predictors of the futures spot price, the basis will be a measure of the expected change in the spot price until maturity (Fama and French, 1987), so shocks can be partially anticipated using the information contained in the basis. This approach is applied to European gas markets, specifically to the natural gas prices in the National Balancing Point (NBP) hub in United Kingdom (UK), in the Title Transfer Facility (TTF) hub in the Netherlands and in the Zeebrugge (ZEE) hub in Belgium. The results obtained confirm what E&S (2008) state, that the risk reduction attained is far higher when considering the expected change in spot prices in the minimum variance hedge ratio calculation. A further objective in this chapter is to compare the hedging effectiveness of unconditional estimations of minimum variance hedge ratios estimated with linear regressions to the conditional estimations of the multivariate GARCH volatility models. To account for seasonality in these conditional models, past values of the basis are introduced as variables in the equations of the models. The risk reduction attained with the conditional models does not outperform the simpler unconditional ones.

In the second chapter of the dissertation, a study of the risk premium in the British natural gas market is implemented. Risk premium can be seen as the expected return of holding a position with futures contracts until delivery. When longer strategies are considered, two alternatives can be implemented: the use of long-term maturity futures contracts with an exact fit to the desired planning timeline or, alternatively, rolling positions in futures contracts with short-term maturity, renewing the position until the desired horizon is attained. For both alternatives, transaction costs have to be taken into account, in addition to the fact that futures contracts with shorter maturities present the greatest liquidity. This could explain why, in NBP, as in many futures markets, trading is concentrated in the front contract and the position is rolled-over until the portfolio's planning horizon is achieved. In this second part, the paper by Szymanowska et al. (2014) is implemented. In their research, the conventional risk premium is divided into two parts: the "spot component" and the "forward component". In our study, the spot component is called the rollover risk premium and the term "forward component" is obtained as the difference between the conventional and the rollover risk premium. In their work, Szymanowska et al. (2014) argue that the long-term conventional risk premium and the cumulative short-term risk premiums differ, since each is related to different risk factors. Accrued short-term risk premiums will be closely related to the spot price risk, while long-term premiums mainly reflect the risk present in the convenience yield. The objective of this study is to quantify the risk premiums in both alternatives and try to explain them with specific risk factors based on equilibrium considerations. The evolution of risk premiums (the conventional risk premium, the accumulated risk premium and the difference between them) is examined over time. For this, a linear regression model is estimated in which the premiums are explained by risk factors such as the standard deviation of the daily average price of the system gas price (System Average Price, SAP), the changes in the levels of natural gas storages in the UK from one month to the previous and the unexpected demand shocks modelled by surprises in the Heating Degree Days (HDD) in winter, when storage levels are at a minimum. And in the case of the difference in risk premiums, in addition to the above factors, open interest is considered. In light of the results, the accrued risk premium in rollover strategies is significantly larger than the conventional risk premiums and increases with time to delivery. Moreover, seasonal patterns are present in all risk premiums analysed—in winter months they are higher and more volatile. Another important result is that risk factors can explain time-varying realized risk premiums, as predicted by theory, and liquidity in the futures market is the most explicative variable for the differences in risk premiums.

Finally, in chapter three, the hedging of the spark spread contract is studied. The spark spread can be defined as the gross profit margin obtained by buying and burning natural gas to produce electricity. The size of this gain depends on the prices of the energy and the efficiency of the generator. The clean spark spread reduces the spark spread with the cost of emitting CO_2 into the atmosphere. The spark spread forward curve is very important for energy producers, since it provides a method for them to ensure power generation profits. Moreover, its average values can indicate to gas generation companies how to maximize profits in their forward transactions by choosing maturities with higher margins. The main objective of the third chapter is the study of the price risk management of electricity and natural gas, as well the determination of the optimal position to take in futures on electricity and natural gas in order to hedge the spark spread risk contract. As in chapter one, changes in the spot spark spread price are partially predictable due to the seasonality of weather, demand and storage levels. This is why, as in chapter one, the E&S (2008) methodology is applied to spark spreads, and the expected changes in the spot spark price are approximated using the information contained in the past values of the basis. The following five cases are studied, both for the spark spread at peak hours and at base hours: (i) hedge ratios for electricity and gas are estimated together; (ii) hedge ratios for electricity and gas are estimated separately in each market; (iii) hedge ratios for electricity and gas are estimated jointly but are restricted to be equal; (iv) hedge ratios for electricity and gas are restricted to take the value 1; (v) hedge ratios for electricity and gas take the value 0, that is, there is no hedging. One of the preliminary results in this chapter is that the spark spread risk and the clean spark spread are two indistinguishable variables from a risk analysis point of view. Furthermore, hedging the spark spread with futures is more difficult than hedging electricity and natural gas price risks with their respective futures contracts, as happens with other commodity spreads, such as the crack spread in Liu et al. (2017).

The remainder of the introduction presents a brief summary, in sections 2, 3 and 4, of the main aspects involved in the origin and evolution of the most significant European natural gas markets. The attention is focused on the British and Dutch markets, the most important and most developed of all the European natural gas markets. In the fifth section, a short description of European electricity market is given. Section 6 presents a short summary of the data and, finally, section 7 summarises the dissertation.

2. The European natural gas market

The European Union began the process of liberalization in natural gas markets in the 1990s. The aim was to achieve a more competitive market and the unification and integration of national markets. The process was initiated with the enactment of the First Gas Directive (98/30/EC). Measures like Third Party Access (TPA) and the unbundling of energy suppliers from network operators set the path towards increased competition. The Second Gas Directive (2003/55/EC) introduced liberalized access in the wholesale market and in the retail market in 2004 and 2007, respectively. The Third Gas Directive (2009/73/EC) was included in the Third Energy Package, which deepened the reforms to achieve a fully liberalized and integrated European natural gas market. It also established the creation of hubs to increase transparency in the pricing process and introduced the Gas Target Model, a framework to develop the future integrated and unified European natural gas market.

Natural gas consumption grew rapidly in the European Union starting in the 1960s, especially after the discovery of natural gas fields in Groningen and the North Sea, reaching a dominant position in the electricity generation mix in some countries. In recent years, this trend has turned around somewhat with the growth in renewable energy.

In Continental Europe, the vast majority of price fixing was through oil-indexed long-term contracts. As these contracts expired, there has been a shift to more inexpensive hub-linked pricing in which the onerous Take-or-Pay (ToP)[1] clause of the former oil-linked long-term contracts is absent.

Each market analysed in this dissertation followed a different path towards a more competitive and open market. The first European natural gas market to begin a process of liberalization was the British after the enactment of the Gas Act (1995). It established the progressive dismantling of the public monopoly of supply and introduced competition into the domestic gas supply. This produced in the early 1990s what was called the “dash for gas” in the industry, a massive shift towards the use of gas in power generation. The new gas-fired power generation facilities needed to supplement their long-term purchase contracts with short-term additional flexible volumes, paving the way to an incipient short-term spot market (Heather, 2010). It also led to the opening of the Interconnector

[1] One of the main characteristics of the long-term contracts is the Take-or-Pay (ToP) clause in which the gas has to be paid for whether delivered or not and the seller has the obligation of making a defined volume of gas available.

pipeline between Belgium and the UK in 1998.

After the Gas Act (1995), the Network Code was developed in March 1996. It set the rules and procedures for third party access to the British gas pipeline grid and created the system of daily balancing, and thus the need for a short-term market (Heather, 2010), and originated the On-the-day Commodity Market (OCM). The latter is designed to allow agents to balance their portfolios on a daily basis using "standardized" contracts. The Network Code also introduced the National Balancing Point (NBP), the first and most important gas hub in Europe. Although the Network Code entailed successful liberalized trading in the natural gas market, it was replaced by the Uniform Network Code (UNC) in 2005. All these legislative changes have made the British gas market the most mature of all the European natural gas markets with a high use of gas in all the end-user sectors (Heather, 2010).

In the Netherlands, the development of the gas market began with the discovery of the Groningen gas field in 1959. Since then, it has been a major gas producer in Europe, despite the seismic problems in 2012. As the most important producer and exporter in the European Union, natural gas plays a prominent role in the Dutch economy. It is the primary source in the energy mix and in power generation. It began the process of liberalization after the United Kingdom, but has achieved a leading role in the European gas markets due to its successful government policies, among other factors, which include its geographical location at the heart of Europe with LNG import facilities, a developed gas transport network, including storage, and a liquid trading hub with an improved market model and balancing regime (Heather, 2012).

In contrast to Britain and the Netherlands, the results in the Belgium gas market have been very different. After the opening of the Interconnector in 1998, Belgium began an incipient process of liberalization with very uneven progress due to some internal characteristics, such as the absence of an integrated network. The Zeebrugge natural gas hub was also developed.

In Germany the implementation of the European Directives was delayed and the process of liberalization of its natural gas markets began in the early 2000s. As stated by the European

Commission in one of its report at the beginning of 2004 (Lohmann, 2006), the progress in the reforms was very disappointing at the beginning and their culmination had many difficulties.

3. European natural gas hubs

A virtual hub is a trading point where natural gas is traded and natural gas prices are set. For all the purchases and sales that are done through the hub, its benchmark prices are used as a reference for financial transactions and risk management of gas portfolios. Trades do not need to be settled in a certain location and can serve a trans-regional area or even a country. Gas negotiated in the hub can be withdrawn from or injected into the grid that it covers at any point. A hub can also be a physical location where various pipelines converge. They are mainly used as transit points for gas transportation and as storage facilities. The Zeebrugge (ZEE) hub in Belgium is an example of a hub with a physical delivery point, while the Tittle Transfer Facility (TTF) in the Netherlands and the National Balancing Point (NBP) in the UK are examples of virtual hubs.

The first hub to be established was the NBP in the UK. Created by the Network Code in 1996 as a balancing mechanism, it is used by the National Grid[2] to balance the system on a daily basis and it is also where shippers[3] nominate their purchases and sales. Initially, its purpose was only to balance the system but it rapidly evolved into a trading point because it could trade on standardized products with high liquidity, such as NBP ICE futures natural gas contracts, which use NBP as a virtual delivery point. Trades at the NBP are made via the OCM trading system, managed by ICE-Endex. It is counterparty to every trade and is responsible for nominating the trades to the National Grid, the body responsible for physically balancing the system. To operate in the NBP, companies have to become shippers; if not, they only can trade on the ICE futures.

Prices established at the NBP are the reference for all UK natural gas. Next, the National Grid levies the differences in transportation costs separately, depending on the geographical area. The OCM system is used as a reference for computing the two most important references in the spot

[2] The British transmission system operator (TSO)
[3] Shippers are commercial players transporting gas in the transmission network.

market: the System Average Prices (SAP) and System Marginal Prices (SMP). These are determined by all the trading in the National Grid gas on a given day in the OCM. The SAP is calculated as the volume-weighted average price of all gas traded via the OCM mechanism. The System Marginal Buy Price (SMBP) is the lowest price traded and the System Marginal Sell Price (SMSP) is the highest one. In the British gas market, since the liberalization process, the pricing has mainly been based on competition factors.

The Title Transfer Facility (TTF) is the virtual hub established in 2003 by Gasunie Transport Services (GTS)[4] where all the natural gas of the Dutch network is traded. In 2011, after some legislative changes, a new market model was introduced with a new balancing regime in which shippers are responsible for keeping their portfolios balanced through buying and selling gas on the TTF. British NBP was the dominant European gas hub for many years, but since 2016 it has been clearly surpassed by the Dutch TTF, not only in terms of total traded volumes but also in several other liquidity metrics, such as churn rate.[5] TTF has become the new reference for natural gas trading in Europe (Heather and Petrovich, 2017). Several factors explain this paradigm shift: its central location in the middle of Europe, its storage and LNG facilities and the excellent network infrastructure with connections to gas fields and other countries, along with the political commitment to develop the Netherlands as the ‘Gas Roundabout’ of Europe (Heather, 2015). All these factors have made it the leading Continental European gas hub.

Zeebrugge (ZEE) is a virtual hub located at the port of Zeebrugge in Belgium. It commenced in 2000, after the inception of the Interconnector. It is used mainly for balancing the day-to-day portfolios but also as a source of cheap gas to fill storage facilities (Abbott, 2016). Although its trading activity increased in 2009, the traded volumes are far below those at TTF or NBP. ZEE is tightly linked to NBP, not only physically but also economically—even the trades are in pence per

[4] GTS is the Transmission System Operator in Netherlands, i.e. the company responsible for the gas pipeline system and its safe operation.

[5] According to Heather (2010), the churn rate is a measure of the number of times a ‘parcel’ of a commodity is traded and re-traded between its initial sale by the producer and final purchase by the consumer. The ‘churn’ is a good measure of a given market’s liquidity and depth and, as a general indication, markets are deemed to have reached maturity when the churn is in excess of 10.

therm. This is a disadvantage because hedgers in Continental Europe increase their foreign exchange risk by trading at ZEE. Another impediment to the development of this trading hub is that it does not cover the entire Belgian gas grid, and also that both the trading and balancing regime are subject to shortfalls and the proration of volumes (Heather, 2012). In 2012, a new natural gas transmission model was introduced that created a single Belgian gas-trading platform named Zeebrugge Trading Point (ZTP), thus offering bilateral trading (OTC) as well as anonymous trading via an exchange. The spot prices are negotiated in ICE-ENDEX, which is also responsible for the clearing services. ZTP futures prices are intended to be the reference for the Belgian natural gas market; however, the development of this new hub is still in its early stages.

The two Germans hubs are NetConnect Germany (NCG), which covers the southern part of Germany, and GASPOOL, which handles the north. They both started operating in 2009 with very limited activity, but this has been increasing; NCG has a considerably higher trading activity and liquidity than GASPOOL. In July 2017, a proposal to merge them was approved by the German government.

4. European natural gas Exchanges

Trading in the gas market can be made centrally on an exchange or over-the-counter (OTC) for both spot and derivatives contracts. The main difference between them is that the OTC trade is a bilateral non-regulated agreement in which the terms are negotiated privately between buyers and sellers, while exchange trading is based on standardized products and the transactions are made anonymously through a centralized trading mechanism, where bids and offers are aggregated and trades allocated with the exchange bearing the counterparty risk. OTC trading can be in standardized products or customized. Most of the trades on gas hubs in Europe are still OTC. However, trading on exchanges has been constantly increasing and is expected to continue growing (European Commission: Quarterly report on European gas markets, 2017).

The most important exchanges in the European Union are the Intercontinental Exchange (ICE) for natural gas in the UK and the European Energy Exchange (EEX)[6] for electricity in Germany. They offer a wide variety of derivative products, both physically and financially settled, such as options and futures contracts with frequencies from daily to yearly periods.

Following the contract specifications, in the ICE the natural gas futures are “Contracts for physical delivery through the transfer of rights in respect of natural gas at the virtual trading point, operated by the transmission system operator. Delivery is made equally each day throughout the delivery period.” If we consider the UK natural gas futures as an example, the trading periods available are: 78-83 consecutive month contracts, 11-13 consecutive quarters, 13-14 consecutive seasons and 6 consecutive years. Trading ceases at the close of business two business days prior to the first calendar day of the delivery month, quarter, season, or calendar year. The size of the contract is “1,000 therms per day per delivery period (i.e. month, quarter, season or year).” The settlement price is “the weighted average price of trades during a fifteen-minute settlement period from 16:00:00 to 16:15:00, London local time. If there is low liquidity during this time, quoted settlement prices (QSPs) will be used to establish the settlement price.” Moreover, “all open contracts are 'marked-to-market' daily, with Variation Margin, as defined in the ICE Clear Europe Clearing Rules, being called for as appropriate.” (ICE, 2017)

According to Heather (2012), the development of the exchanges has contributed to the growth of the hubs, especially in Britain and the Netherlands with the ICE and APX-Endex exchanges respectively, although the OTC market represents the most important market across the Continental Europe hubs with approximately 60% of the total traded volumes. Only in the NBP are the exchange-traded volumes now almost equal to the OTC-traded volumes. Notwithstanding this, the exchanges are growing in Continental Europe (Russo, 2017).

5. European electricity markets

Because of the interplay between all the energy sources, and especially those involved in power

[6] The spot market trading both in ICE and EEX is done through their subsidiary companies, ICE Endex and Powernext-Pegas, respectively.

generation, some important features of the European electricity markets and their interaction with the natural gas market will now be discussed.

The European electricity markets have experienced great changes in recent years. The transition towards a low-carbon economy has meant a growing role for renewable energy sources. The completion of a fully-functioning, interconnected and integrated internal energy market would produce diverse benefits for consumers, such as lower prices, hence it is one of the priorities of the European Union. To achieve this, the Commission has promoted the EU target electricity model (TEM) to achieve a reliable, sustainable and affordable system. The target model is based on two broad principles: energy-only regional markets, preferably organised on a zonal basis, in which the revenues of power generators depend primarily on the price for each marginal unit of energy supplied; and market coupling, which is a way of linking zonal day-ahead spot markets into a virtual market, so that the lowest priced bids are accepted up to the point where congestion constraints limit further trade (Keay, 2013).

According to Jamasb and Pollitt (2005), the liberalization of the European electricity sector was carried out at two parallel levels. The first one was under Electricity Directives in which electricity companies from across the EU member states were empowered to compete with the so-called national incumbents. At the second level, the interconnections between member states were improved by developing cross-border trading rules and expanding cross-border transmission links, which will ultimately reduce cross-border transport costs and increase competition.

The First Electricity Directive in 1996 (Directive 96/92/EC) set a progressive pathway towards competition with the market opening up to new competitors and choice becoming available for large (industrial) electricity consumers. It also required the unbundling of previously vertically integrated monopolistic companies and the creation of new market participants, especially in terms of transmission and distribution system operators, which had to be separate from the competitive parts of the electricity sector (Jakovac, 2012). The implementation was very different among the member states, especially concerning the degree of openness of the market and the access to the network.

The second Electricity Directive (2003/54/EC) deepened the reforms strengthening the EU's energy policy, ensuring the supply of electricity to all consumers, the full opening of the markets, higher service standards and business efficiency, as well as the security of supply and lower electricity prices. It also toughened the network access regulations by requiring the establishment of an independent regulatory body, and boosted environmental protection and the promotion of renewable resources along with the protection of consumers' fundamental interests (Jakovac, 2012).

The Third Electricity Directive (2009/72/EC) was aimed at further liberalising the internal electricity market, enhancing competitiveness and, especially, protecting the consumer. Concerning the unbundling process, the Directive established full separation between generation activities and the transmission sector; the TSO and the network owner must be completely separated. It also created the Agency for Cooperation of Energy Regulators to solve cross-border conflicts and boost cooperation in decision-making.

The first country to begin its liberalization process was the UK in the 1980s, before the enactment of the directives described. The degree of success in the process has been varied depending on the country and the previously existing market structure: a competitive system in the UK, a structure of multiple regional monopolies in Germany or the centralized market in France.

With regard to the electricity pricing process in the analysis carried out in chapter three, spot prices are determined by the intersection of the supply and demand curves at an auction in which the price for the following day is settled. Power producers make their electricity offers according to their short-term marginal costs, principally fuel and CO_2 costs. Offers are then sorted from lowest to highest, obtaining the merit order curve, that is, the electricity offer curve. As renewables offer electricity at nearly zero marginal costs, they are the first to enter the merit order, followed by nuclear energy, coal or gas (depending on the country and the commodity price, although in the last few years, it is usually coal before gas for the UK and Germany and gas for the Netherlands) and fuel oil plants. The price setting units are different in hours of high (peak hours) and constant demand (base hours). In nearly all European countries, natural gas has been displaced to be a back-up source in the case of the interruptible supply of renewables.

As for trading, both spot prices and futures prices, it is carried out in the same European exchanges that also offer gas contracts: ICE-Endex, EEX and Powernext.

6. Data

The data used in this dissertation are mainly natural gas and electricity prices. The natural gas prices are the natural gas hubs prices obtained from the exchanges or from data provider companies. In the first chapter, natural gas spot and futures prices are obtained from Platts and ICE, respectively. In the second chapter, the data for the UK are also from Platts and ICE, and the SAP price is retrieved from the National Grid website. In the third chapter, German electricity spot and futures prices are taken from the EEX. The British and Dutch spot and futures prices are collected from Reuters and APX-Endex (now ICE-Endex), respectively. In each chapter there is detailed information about the sample period and the construction of the time series employed, as well as the particular origin of all the data sets used.

7. Summary of the chapters

This dissertation has covered different aspects of the European natural gas and electricity markets, in particular properties affecting hedging performance, such as seasonality in variance and prices. Likewise, natural gas risk premium has been examined, including its relationship with risk variables and its decomposition in a roll-over risk premium and a liquidity risk premium.

Chapter 1: European natural gas seasonal effects on futures hedging. This chapter studies and designs futures hedging strategies in European natural gas markets (NBP, TTF and Zeebrugge). A common feature of energy prices is that conditional mean and volatility are driven by seasonal trends due to weather, demand, and storage level seasonalities. This chapter follows and extends the Ederington and Salas (2008) framework and considers seasonalities in mean and volatility when minimum variance hedge ratios are computed. Our results show that hedging effectiveness is much higher when the seasonal pattern in spot price changes is approximated with lagged values of the basis (futures price minus spot price). This fact remains true for short (a week) and long (one, three and six months) hedging periods. Furthermore, volatility of weekly price changes also has a seasonal pattern and is higher in winter than in summer. A simple volatility seasonal model that is based on sinusoidal functions on the basis improves the risk reduction obtained by strategies in which hedging ratios are estimated with linear regressions. Seasonal hedging strategies, linear regression based strategies, or even a naïve position, perform better than more sophisticated statistical methods.

A preliminary version of this paper was presented at the X Spanish Association for Energy Economics (Tenerife, Spain, January 2015), and at the 6th Workshop on Energy Markets (Valencia, Spain, March 2015). The chapter has been published in a preliminary version as Working Paper (Nota di Lavoro 2015.010) by Fondazione Eni Enrico Mattei (FEEM). The final version was submitted to Energy Economics in November 2014, and it was accepted in April 2015.

Chapter 2: Analysis of risk premium in UK natural gas futures. In many futures markets, trading is concentrated on the front contract and positions are rolled-over until the strategy horizon is attained. In this paper, a pair-wise comparison between the conventional risk premium and the accrued risk premium in rolled-over positions on the front contract is carried out for UK natural gas futures. Several novel results are obtained. Firstly, and most importantly, the accrued risk premium in rollover strategies is significantly larger than conventional risk premiums and increases with the time to delivery. Specifically, for strategy horizons between three and six months, this difference increases from 1% to 10% (or from 4% to 20% in annualized returns). Secondly, risk premium in day-ahead forwards has been measured in this market. The average value of the day-ahead risk premium is 0.5% per day and it is statistically significant. Thirdly, all risk premiums are significantly larger and more volatile in winter. Finally, risk premium time-variation is analysed using a regression model. It is shown that reservoir shocks, demand shocks and spot price volatility are significant predictors and their signs reflect equilibrium models for storable commodities.

A preliminary version of this paper was presented at the 7th Workshop in Energy Markets (Valencia, Spain, March 2016), at the Energy and Commodity Finance Conference 2016 (Paris, France, May 2016) and at the XXIV Finance Forum (Madrid, Spain, July 2016). The chapter has been published in a preliminary version as Working Paper (Nota di Lavoro 2016.006) by Fondazione Eni Enrico Mattei (FEEM). The final version was submitted to International Review of Economics and Finance in December 2016.

Chapter 3: Hedging spark spread risk with futures. This chapter discusses spark spread risk management using electricity and natural gas futures. We focus on three European markets with varying shares of natural gas in the fuel mix: Germany, the United Kingdom, and the Netherlands. We find that spark spread returns are partially predictable and, consequently, the Ederington and Salas (2008) minimum variance hedging approach should be applied. Hedging the spark spread is more difficult than hedging electricity and natural gas price risks with individual futures contracts. Whereas spark spread risk reduction for monthly periods produces values of between 20.05% and 48.90%, electricity and natural gas individual hedges attain reductions ranging from 31.22% to 69.06%. These results should be of interest to agents in those markets in which natural gas is part of the electricity generation mix.

A preliminary version of this paper was presented at the 8th Workshop in Energy Markets (Valencia, Spain, March 2017) and at the 5th International Symposium on Environment and Energy Finance Issues (ISEFI-2017) (Paris, France, May 2017). The chapter has been published in a preliminary version as Working Paper (WP-EC 2017-01) by Instituto Valenciano de Investigaciones Económicas (IVIE). The final version was submitted to Energy Policy in July 2017, and it was accepted in November 2017.

8. Stays, grants and prizes

I developed my PhD dissertation at the University of Valencia (Department of Financial and

Actuarial Economics and Department of Corporate Finance, Valencia, Spain), as a PhD student from the University.

During my PhD I have participated in different workshops and research stays:

- Research stay at the German Institute for Economic Research – DIW (Berlin, Germany) from 4 January 2013 to 28 April 2013
- This PhD dissertation was presented at Jornadas de seguimiento de tesis Doctorales, (Bilbao) on 19 December 2014.
- Discussing the study entitled "Los Costes de la Energía en la Industria del País Vasco" at the 6th research workshop on energy markets (Valencia) on 27 March 2015.

The research was financially supported by:

- An F.P.U. (Formación del Profesorado Universitario) Grant from the Ministry of Education (Spain) during the period 16 October 2006 – 4 June 2013.
- A Mobility Grant from the Ministry of Education (Spain) for the stay in Berlin.
-The Spanish Ministry of Economy and Competitiveness through the research project Quantitative Finance (ECO2013-40816-P).

References

Abbott, M. (2016). The Economics of the Gas Supply Industry, Routledge (Oxford).

Cludius J., Hermann H., Matthes F.C. & Graichen V. (2014). The merit order effect of wind and photovoltaic electricity generation in Germany 2008–2016: estimation and distributional implications. Energy Economics, 44, 302–313.

Ederington, L. H. (1979). The hedging performance of the new futures markets. The Journal of Finance, 34(1), 157-170.

Ederington, L. H. & Salas, J. M. (2008). Minimum variance hedging when spot price changes are partially predictable. Journal of Banking and Finance, 32, 654-663.

European Commission (2017). Quarterly Report on European Gas Markets. Volume 10 (issues 1 and 2; first and second quarter of 2017).

Fama, E. F. & French, K. R. (1987). Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage. Journal of Business, 60, 55-74.

Heather, P. (2010). The evolution and functioning of the traded gas market in Britain. Oxford Institute for Energy Studies, NG 44.

Heather, P. (2012). Continental European Gas Hubs: Are they fit for purpose? Oxford Institute for Energy Studies, NG 63.

Heather, P. (2015). The evolution of European traded gas hubs. The Oxford Institute for Energy Studies. NG 104.

Heather, P. & Petrovich, B. (2017). European traded gas hubs: an updated analysis on liquidity, maturity and barriers to market integration. The Oxford Institute for Energy Studies. OIES Energy Insight.

ICE (2017). UK Natural gas futures. International Exchange, Available at: https://www.theice.com/products/910/UK-Natural-Gas-Futures. Access on: 24/11/2017.

Institute of Energy for S.E. Europe (2014) The Outlook for a Natural Gas Trading Hub in SE Europe.

Jakovac, P. (2012). Electricity Directives And Evolution Of The EU Internal Electricity Market. Economic Thought and Practice, 1.

Jamasb, T. & Pollitt, M. (2005). Electricity Market Reform in the European Union: Review of Progress toward Liberalization & Integration. The Energy Journal, 26, 11-41.

Keay, M. (2013). The EU “Target Model” for electricity markets: fit for purpose. Oxford Institute for Energy Studies.

Liu, P., Vedenov, D. & Power, G. J. (2017). Is hedging the crack spread no longer all it's cracked up to be? Energy Economics, 63, 31-40.

Lohmann, H. (2006). The German Path to Natural Gas liberalisation: Is It a Special Case? The Oxford Institute for Energy Studies, NG 14.

Russo, M. (2017). Essays in the evolving European natural gas markets. Doctoral dissertation, City, University of London.

Sensfuß, F., Ragwitz, M. & Genoese, M. (2008). The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy policy, 36(8), 3086-3094.

Serena, R. (2014). The European Electricity Market Liberalization. Master's Thesis, Tilburg University.

Szymanowska, M., De Roon, F., Nijman, T. & Van den Goorbergh, R. (2014). An Anatomy of Commodity Futures Risk Premia. The Journal of Finance 69, 453-482.

Chapter I

EUROPEAN NATURAL GAS SEASONAL EFFECTS ON FUTURES HEDGING

1. Introduction

A common feature of natural gas prices is that spot price changes are partially predictable due to weather, demand, and storage level seasonalities. Further to this, the volatility of natural gas prices is seasonal. In winter, the active storage management is less flexible and price jump buffers are more difficult than in summer. Moreover, higher marginal cost production, demand inelasticity, and winter weather shocks trigger price jumps that produce a higher volatility than in summer.[1]

Ederington and Salas (2008) have adapted the standard minimum variance hedge ratio approach (Ederington, 1979) to the case where spot price changes are partially predictable. In this context, they show that the riskiness of the spot position is overestimated, the achievable risk reduction is underestimated, and more efficient estimates of the hedge ratios are obtained. Ederington and Salas (2008) propose to use the basis (futures price minus the spot price) at the beginning of the hedge as the information variable to approximate the expected spot price change. If futures prices are unbiased predictors of futures spot price, the basis will be a measure of the expected change in the spot price until maturity (Fama and French, 1987). This approach is applied to European gas markets for the first time in this paper.

The UK natural gas market is the most liquid market in Europe.[2] The vast majority of gas contracts are over-the-counter but the regulated futures market is growing in importance (Heather, 2010). The futures British gas market is operated by InterContinental Exchange (ICE) Europe. The ICE natural gas futures contract for NBP was launched in January 1997 and has become the benchmark for natural gas trading in Britain and in continental Europe.[3] Continental gas markets were developed

[1] See Mu (2007), Suenaga et al. (2008), Alterman (2012), Henaff et al. (2013) and Efimova and Serletis (2014).

[2] Liberalization of the natural gas market began in the UK with the 1995 Gas Act. The following year, the Network Code created the National Balancing Point (NBP) hub enabling third party access to the British gas network. The National Transition System then changed the balancing regime from monthly to daily. Thereafter, all gas in the UK must be traded through the NBP hub. The Network Code also included the NBP`97 contract, a common standardized trading contract required for trading gas in the British market and in which all the natural gas agreements must be based. This contract, along with changes in the balancing, enabled the development of the British hub. Important changes in the contractual conditions and trading system were introduced in the British natural gas market in 2004-2005 after the Enron and TFX collapse, resulting in a new regulation, the Uniform Network Code in 2005. The equivalent of NBP`97 is ZBT`2000 in Zeebrugge and EFET for TTF.

[3] According to the International Energy Agency (IEA, 2013) more than 50% of all the gas sold in Europe is priced linked to hubs – with prices linked to oil becoming less important in long-term contracts.

following the path the British had marked. The UK and continental Europe are linked through *The Interconnector* – a gas pipeline which connects the UK gas entry point at Bacton to the Belgian port of Zeebrugge (ZEE henceforth). It has been open since 1998 and enables the flow of gas between British and continental markets. Since its launch, UK prices have converged progressively to continental prices (Heather (2012)).

The Title Transfer Facility (TTF, henceforth) was established in 2003 in the Netherlands. It is the virtual trading point for the Dutch natural gas market. It is the most developed natural gas market in continental Europe, comparable to NBP for hedging and balancing purposes. TTF is becoming the leading gas hub in Europe, because of its location in the heart of Europe, LNG import facilities, and storage capacity. Futures contracts on TTF and ZEE are also negotiated on the Intercontinental Exchange (ICE).

There are several questions in the literature on risk management in energy markets that we will try to answer for the special case of European natural gas markets. We will focus on the existence of seasonal patterns in first and second moments of price returns and the implications for futures hedging. In a similar context, Chang et al. (2010) found that futures hedging effectiveness of a covariance model specification can change depending on the market trend (bull/bear) in energy markets (oil and gasoline). The influence of seasonality in energy prices for hedging purposes has also been studied in Suenaga et al. (2010). In their opinion, seasonal hedging turns out to be quite discretional under strong seasonality in prices. Long spot positions from the peak to off-peak price season would be senseless and it is better not to have these positions. Nevertheless, in our opinion, risk measures should take into account the Ederington and Salas (2008) framework, where predictable seasonal price movements are incorporated to compute the unexpected spot price movement, both in the hedging ratio computation and in the measurement of hedging effectiveness. Furthermore, the influence of energy variance seasonality on futures hedging performance has not yet been explored. To the best of our knowledge, this is the first paper dealing with this issue and we have checked if hedge ratios and their effectiveness have a significant seasonal pattern. In addition, in the last few years non-conventional shale gas has become abundant and represents a downward pressure on winter prices. Finally, the increased number of cooling systems and the growing use of natural gas as a fuel are raising summer prices (see Henaff et al. (2013)). Both effects reduce price seasonality on the US market. It would be interesting to check if seasonality in mean and volatility persists in European natural gas markets.

This chapter presents empirical results on hedging natural gas price risk with futures when an early cancellation of futures positions is made. The empirical study considers the three most important benchmarks in European natural gas markets: NBP, ZEE and TTF. Using monthly futures contracts and daily spot prices, several combinations of hedging period lengths (one week, and one, three, and six months) are examined. Results can be summarized as follows: (i) hedging performance improves as hedging duration increases. That is, one month hedges perform better than one-week hedges and so on; (ii) minimum variance hedge ratios are unconditionally estimated with the Ederington and Salas (2008) approach for all hedge periods and conditionally estimated for weekly hedging periods with the multivariate GARCH model proposed by Engle and Kroner (1995). We further designed a simple conditional covariance model using sinusoidal functions. The highest risk reduction for the NBP and ZEE is obtained with the seasonal model. For the TTF market, the simple naïve strategy maximizes risk reduction. The OLS hedge ratio estimation proposed by Ederington and Salas (2008) produces the second best risk reduction (only slightly lower). The worst performance is found for all the tested GARCH covariance models. Consequently, it does not seem that improving statistical price modeling will guarantee better performance in our empirical application; (iii) it is found that the basis has a clear seasonal pattern with positive on-peak values in winter and negative off-peak values in summer. The basis has an important predictive power for explaining spot price changes (between 10% and 50%), consequently, the Ederington and Salas (2008) framework perfectly suits our experiment and unexpected spot price changes must be computed using the information contained in the basis; (iv) a strong and persistent seasonal pattern in both spot and futures returns volatility exists, but we do not find any significant seasonal pattern on futures hedge ratios and their effectiveness in reducing risk. This seasonal pattern is captured more smoothly with a sinusoidal function in the basis as the basis is more stable than price returns; (v) it is shown that very large risk reductions are achievable by using the approach proposed in Ederington and Salas (2008) and optimizing the futures contract selection as described above. Specifically, risk reduction values vary between 30% and 90% – depending on the hedging duration (one week to six months) and the analyzed sub-period (in-sample and out-of-sample sub-periods).

This chapter is divided into seven sections. In Section 2, hedging ratios and their effectiveness measure are defined. In Section 3, the econometric model used to obtain conditional estimates of hedging ratios is presented. Section 4 contains the data description and some preliminary analysis. Estimation and hedging results are shown in Section 5. The chapter finishes with conclusions and cited references.

2. The Minimum Variance Hedge Ratio

Alexander et al. (2013) argue that the *minimum variance* (MV henceforth) framework has several advantages over *optimal hedging* (OH henceforth). OH is based in normality of mean-variance utility functions. These are unrealistic hypotheses. Assuming futures prices are martingale, the high volatility in energy prices points to the MV as the essential problem (see Alexander et al. 2013, page 699). Furthermore, Cotter and Hanly (2013) conclude that in the oil market the OH approach is not sufficiently different to warrant using a more complicated utility-based approach as compared with the simpler MV. Cotter and Hanly (2010) estimate the time-varying coefficient of relative risk aversion in energy markets by obtaining values between 0 and 1.25 (quite low values compared to financial markets). Ex-ante and using a mean variance utility function with the average value of lambda (risk aversion parameter) makes MV the best performing strategy for weekly and monthly hedges and for long and short hedgers. Based on this evidence from the energy markets we use the MV framework. Below we describe the MV framework and the extension proposed in Ederington and Salas (2008).

The conventional minimum variance hedge ratio is defined in a one-period model. At the beginning of the period, or 't', an individual is committed to a given position in the spot market. To reduce the risk exposure, the individual may choose to hedge at time 't' in the futures market with the same underlying asset. At the end of the period, say, '$t + 1$', the hedger's result per unit of spot is calculated as follows

$$x_{t+1} = \Delta S(t) - b_t \, \Delta F(t,T) \tag{1}$$

where x_{t+1} is the value variation between t and t+1, $\Delta S(t) = (S(t+1) - S(t))$ is the spot value variation, $\Delta F(t,T) = (F(t+1,T) - F(t,T))$ the futures value variation of a futures contract maturing at T, and b_t is the hedging ratio. If b_t is positive (negative), short (long) positions are taken in futures. The hedger will choose b_t to minimize the risk associated with the random result x_{t+1}. We use realized returns instead log returns because we agree with the Alexander et al. (2013) methodology on several points. These authors argue that "...for assets with prices that can jump, log returns can be highly inaccurate proxies for percentage returns even when measured at the daily frequency. Additionally, since the hedged portfolio can have zero value, even its percentage return may be undefined. Thus, our hedging analysis is based on profit and loss (P&L) rather than on log or percentage returns". A standard way to measure risk in economics is by using the variance conditional on the available information at time t. The risk of a hedge strategy is calculated as the variance of x_{t+1},

$$VAR[x_{t+1}|\psi_t] = VAR[\Delta S(t) - b_t \Delta F(t,T)|\psi_t] \tag{2}$$

The most used definition for the optimal hedge ratio[4] is the *minimum variance hedge ratio* that can be obtained by minimizing equation (2), which is the following:

[4] For an excellent review on futures hedging, see Lien and Tse (2002).

$$b_t = \frac{cov(\Delta S(t), \Delta F(t,T) | \psi_t)}{var(\Delta F(t,T) | \psi_t)} \quad (3)$$

where second moments are conditioned to the information set available at the beginning of the hedging period, ψ_t. When an unconditional probability distribution is used, the hedge ratio in equation (3) can be estimated from a linear relationship between spot and futures returns. That is, estimating the linear relationship appearing in equation (1) by ordinary least squares (OLS henceforth) but adding an intercept and white noise

$$\Delta S(t) = a + b\Delta F(t,T) + \varepsilon(t) \quad (4)$$

In this case, the OLS estimator of b is the unconditional definition of the optimal hedge ratio appearing in equation (3) (Ederington, 1979).

Ederington and Salas (2008) have adapted the above approach to the case where spot price changes are partially predictable and futures prices are unbiased estimators of future spot prices. In this context, they show that the riskiness of the spot position is overestimated and the achievable risk reduction underestimated. Under their approach, the unexpected result of the hedge in equation (1) can be reformulated as

$$x_{t+1} = (\Delta S(t) - E[\Delta S(t) | \psi_t]) - b_t' \Delta F(t,T) \quad (5)$$

The risk of the hedge strategy in equation (2) is reformulated as

$$VAR[x_{t+1} | \psi_t] = VAR[(\Delta S(t) - E[\Delta S(t) | \psi_t]) - b_t' \Delta F(t,T) | \psi_t] \quad (6)$$

and the minimum variance hedge ratio obtained after minimizing equation (6) is

$$b_t' = \frac{cov((\Delta S(t) - E[\Delta S(t)|\psi_t]), \Delta F(t,T)|\psi_t)}{var(\Delta F(t,T)|\psi_t)} \quad (7)$$

Ederington and Salas (2008) propose using the basis (futures price minus the spot price) at the beginning of the hedge as the information variable to approximate the expected spot price change. If futures prices are unbiased predictors of futures spot price, the basis will be a measure of the expected change in the spot price until maturity (Fama and French, 1987). An unconditional estimate of the hedge ratio in equation (7) can be obtained by estimating the following linear regression using OLS

$$\Delta S(t) = a' + b'\Delta F(t,T) + \lambda(F(t,T) - S(t)) + \varepsilon'(t) \quad (8)$$

where $\lambda(F(t,T)–S(t))$ is used to estimate $E[\Delta S(t)|\psi_t]$. Ederington and Salas (2008) show that OLS estimation of equation (8) produces an unbiased and more efficient estimation of the unconditional minimum variance hedge ratio (b') than that obtained by using equation (4). This is providing that the expected change in the spot price is perfectly approximated with the product between the basis at the beginning of the hedge and its estimated coefficient (namely $\hat{\lambda}(F(t,T) - S(t)) = E[\Delta S(t)|\psi_t]$).

2.1. Measuring hedging effectiveness

The risk reduction is computed to compare the hedging effectiveness of each strategy. Furthermore, *ex post* and *ex ante* results are distinguished by splitting the data sample into two parts. In the first part, the hedging strategies are compared *ex post*, whereas in the second part, an *ex ante* approach is used. That is, in the *ex ante* study, strategies are compared using forecasted hedge ratios, and models are estimated every time a new observation is considered. The variance of a hedge strategy is calculated as the variance of the hedged portfolio – as shown in equation (6). In this equation, the OLS estimated approximation of the expected spot price change using the basis is introduced ($\hat{\lambda}\left(F(t,T)-S(t)\right)=E\left[\Delta S(t)\middle|\psi_t\right]$). The risk reduction achieved for each strategy is computed by comparison with the variance of the spot position (b_t = 0 for all t in equation (6)).

In the empirical application presented in Sections 4 and 5, futures with different maturities ($F(t,T_i)$ with i =1, 3, and 6 months; and $T_i = t + i$) are considered to hedge the spot price variation. Furthermore, four hedging lengths are considered: one week and 1, 3, and 6 months. Table 1 shows the four types of hedges carried out in this paper, one per row. This typology enables a study of the influence of the hedging length. It is expected that hedging performance improves as hedging length increases.[5] The second and third columns contain the spot and futures price variations implied in each hedging operation. Finally, the last column in Table 1 reports the basis used to approximate the expected spot price change in equations (6) and (8). It is important to note that only one basis is used per hedging period.[6]

In the empirical application in Section 5, five hedging strategies are compared. The hedging ratio obtained after estimating equation (4) is labeled 'OLS without basis' – and the hedging ratio obtained after estimating equation (8) is identified as 'OLS with basis'. In the following section, the alternative conditional covariance model enables the estimation of the hedging ratio appearing in equation (7). The first strategy is labeled as 'seasonal', the second strategy 'seasonal-basis' and the third strategy is identified as 'BEKK'. Hedging analysis is completed with the 'naive' hedging ratios, that is, a hedge where futures positions have the same size, but the opposite sign to the position held in the spot market (*i.e.* b_t = 1 for all t).

To test if the difference in hedging reductions are statistically significant, we performed White's

[5] Lindahl, 1992.

[6] The unhedged spot price risk will be measured as $\mathrm{VAR}[\Delta^k S(t)-\hat{\lambda}(F(t,T_k)-S(t))]$ after estimating λ by OLS from the adapted equation (8): $\Delta^k S(t)=a'+b'\Delta^k F(t,T_i)+\lambda(F(t,T_k)-S(t))+\varepsilon'(t)$ for k= 1 week and 1, 2, and 3 and i= 1, 2, and 3 months and $i > k$. In the *ex ante* study, the unhedged spot price risk measure is computed by repeating this procedure each time a new observation is considered, obtaining a vector of λ coefficients that is as large as the out-of-sample period.

reality check as described in Lee and Yoder (2007) – but using Equation(6) as a risk measure instead Equation(2) because we are applying the Ederington and Salas (2008) approach. For technical details we referred to Lee and Yoder (2007a), Lee and Yoder (2007b) and White (2000). Specifically, the variance of the estimated optimal hedged portfolio in the *ex ante* study under the E&S (2008) approach is computed as

$$VAR\left[\left(\Delta S(t)-\hat{\lambda}_t\left(F(t,T)-S(t)\right)\right)-\hat{b}_t'\Delta F(t,T)\right] \tag{9}$$

where $\hat{\lambda}_t$ and $\hat{b}_t'$ are predicted parameter estimations conditioned on the information available at t as previously described. For each pair of hedging strategies, and for each observation included in the *out of sample* period, the following performance measure was computed

$$\hat{f}_{k,t+1}=\left[\left(\Delta S(t)-\hat{\lambda}_t\left(F(t,T)-S(t)\right)\right)-\hat{b}_{k,t}'\Delta F(t,T)\right]^2+\left[\left(\Delta S(t)-\hat{\lambda}_t\left(F(t,T)-S(t)\right)\right)-\hat{b}_{BM,t}'\Delta F(t,T)\right]^2 \tag{10}$$

where $\hat{b}_{BM,t}'$ is the estimate of the hedging ratio strategy used as benchmark; that is, the hedging strategy with the lowest risk reduction in each pair of strategies. And $\hat{b}_{k,t}'$ is a hedging ratio corresponding to the set of all possible hedging strategies with better risk reductions than the compared benchmark strategy. White's reality check is based on the following performance statistic

$$\bar{f}=\frac{1}{n}\sum_{t=R}^{T}\hat{f}_{t+1} \tag{11}$$

where n is the number of observations in the *out of sample* experiment, that is $n = T - R$. The null hypothesis that the best performing hedging strategy from each pair of possible strategies considered has no predictive superiority over the worse performer in each pair is given by

$$H_0 : E\left[f_k^*\right] \leq 0 \tag{12}$$

where f_k^* is the true performance value for each model applied to the data. Following White (2000), White's reality check is implemented with the stationary bootstrap resampling method of Politis and Romano (1994) in which pseudo-time series are generated by resampling blocks of random length drawn from a geometric distribution. This procedure is repeated to generate an approximate sampling distribution of the $\bar{f}$ performance measure. To apply the stationary bootstrap method of Politis and Romano (1994), the smoothing parameter q and the number of resamplings are set to 0.5 and 10000, respectively.[7]

3. The econometric framework

One of the objectives of this paper is to compare the hedging effectiveness of conditional and unconditional minimum variance hedge ratio estimates. To obtain conditional estimates of the second moments, a two-step estimation procedure is followed. Firstly, a model in means is estimated and then the residuals of this model are taken in the second step as an input to model the conditional variance. In a similar empirical study, Efimova and Serletis (2014) model daily natural gas prices in the US by introducing storage levels and temperature in the mean equation to cope with seasonality in prices. As the basis contains all this information we have introduced the lagged value of the basis in the model. Furthermore, as the basis can been understood as an equilibrium model deviation between spot and futures price equilibrium (Viswanath, 1993; Lien, 1996), we propose the following vector error correction model to clean any autocorrelation

$$\begin{aligned} \Delta^k S(t) &= \gamma_1 + \gamma_{10}\left(F(t,T_k) - S(t)\right) + \sum_{\tau=1}^{p} \gamma_{11\tau} \Delta^k S(t-\tau) + \sum_{\tau=1}^{p} \gamma_{12\tau} \Delta^k F(t-\tau,T_i) + \varepsilon_{1,t+k} \\ \Delta^k F(t,T_i) &= \gamma_2 + \gamma_{20}\left(F(t,T_k) - S(t)\right) + \sum_{\tau=1}^{p} \gamma_{21\tau} \Delta^k S(t-\tau) + \sum_{\tau=1}^{p} \gamma_{22\tau} \Delta^k F(t-\tau,T_i) + \varepsilon_{2,t+k} \end{aligned} \tag{13}$$

[7] We acknowledge the insightful suggestion to introduce White's reality check made by one of the referees.

where $\Delta^k S(t) = (S(t+k) - S(t))$ with $k = 1$ week and 1, 3 and 6 months; $\Delta^k F(t,T_i) = F(t+k,T_i) - F(t,T_i)$ with $T_i = t+i$; $i = 1$, 3, and 6 months and $k < i$; represent the k differences in futures prices when 'i' periods remain to 'delivery' or settlement – approximately as futures positions are closed just before maturity (note that $F(t+k,T_i) \neq S(t+k)$ when $k = i$); the gammas are the parameters to estimate; p is the lag of the VAR and is chosen by minimizing the Hannan and Quinn (1979) information criteria, thereby eliminating any autocorrelation patterns. The VAR model is estimated by OLS (Engle & Granger, 1987). The vector of residuals, $\varepsilon_{t+k} = (\varepsilon_{1t+k}, \varepsilon_{2t+k})'$, are saved and used as observable data to estimate seasonal and multivariate GARCH covariance models. This two-step procedure (Kroner & Ng, 1998; Engle & Ng, 1993) reduces the number of parameters to estimate in the second step, decreases the estimation error, and enables a faster convergence in the estimation procedure. In the VAR model in equation (13), the basis described in the last column of Table 1 appears as an external variable. The basis can be seen as an error correction term when spot and futures prices are cointegrated, as this is the case (Viswanath, 1993; Lien, 1996). The inclusion of the basis in the VAR specification implies an efficient conditional estimation of the minimum variance hedge ratio (see equation (7)) as it contains important information for anticipating spot price changes. A robustness check was made regarding the adequacy of the proposed model in equation (13), and an expanded model including an annual sinusoidal trend was estimated. The expanded estimated model did not report any sinusoidal trend coefficient significantly different to zero at one per cent of significance level. Moreover, the computation of the likelihood ratio test between the expanded model and the model in equation (13) rejects the significance of any expansion.

3.1. The BEKK covariance model

The number of published papers modeling conditional covariance is quite small compared to the enormous bibliography on time-varying volatility. The three most widely used models are: (1) the VECH model proposed by Bollerslev *et al*. (1988); (2) the constant correlation model, CCORR, proposed by Bollerslev (1990) and; (3) the BEKK model of Engle and Kroner (1995). Each model imposes different restrictions on the conditional covariance and can lead to substantially different conclusions in any application that involves forecasting conditional covariance matrices.[8] Asymmetries are introduced following the Glosten *et al.* (1993) approach. This is the most common method for introducing asymmetries in multivariate GARCH modeling (Gagnon and Lypny, 1995; Hendry and Sharma, 1999; Bekaert & Wu 2000). In the empirical applications appearing in the following sections, we only report results for the asymmetric version of the BEKK model. We have tested the above mentioned conditional variance models and many of its variants, but we decided to skip these results as the conclusions of the paper will not change.

The two-dimensional asymmetric BEKK model in its compacted form can be written as follows:

$$H_t = C'C + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + G'\eta_{t-1}\eta_{t-1}'G \tag{14}$$

where C, A, B and G are 2×2 matrices of parameters, H_t is the 2×2 conditional covariance matrix, and ε_t and η_t are 2×1 vectors containing the shocks and threshold terms series. Therefore, the unfolded covariance model is written as follows:

$$\begin{bmatrix} h_{11t} & h_{12t} \\ . & h_{22t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11t-1} & h_{12t-1} \\ . & h_{22t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1t-1}^2 & \varepsilon_{1t-1}\varepsilon_{2t-1} \\ . & \varepsilon_{2t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' \begin{bmatrix} \eta_{1t-1}^2 & \eta_{1t-1}\eta_{2t-1} \\ . & \eta_{2t-1}^2 \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \tag{15}$$

where c_{ij}, b_{ij}, a_{ij}, and g_{ij} for all i, j = 1, 2 are parameters, ε_{1t} and ε_{2t} are the unexpected shock series

[8] Myers (1991) and Baillie and Myers (1991) have used the VECH specification, without the asymmetric extension, in spot-futures covariance modelling for hedging purposes for various agricultural commodities. The CCORR model has often been used for modelling spot-futures covariance dynamics. Some examples are: Cecchetti *et al.* (1988) in public debt; Kroner and Sultan (1993) in currencies; and Park and Switzer (1995) in stock indexes. The BEKK model has been used in Baillie and Myers (1991) (without asymmetries), and Gagnon and Lypny (1995), in modelling spot-futures covariance for agricultural commodities and interest rates, respectively.

obtained from equation (13). $\eta_{1t} = \max\ [0,-\varepsilon_{1t}]$ and $\eta_{2t} = \max\ [0,-\varepsilon_{2t}]$ are the Glosten et al. (1993) dummy series capturing negative asymmetries from the shocks and h_{ijt} for all i, j = 1, 2 are the conditional second moment series. The dot [.] appearing in some matrices in equation (11) means that these matrices are symmetric.

3.2 The seasonal covariance model

Benth and Benth (2007) propose a truncated Fourier series expansion describing the conditional variance of Stockholm temperature. In a similar way, we apply this idea to the bivariate case. Our empirical results for weekly data frequency show that there is only an annual seasonal pattern and any higher frequency seasonality is significant. Therefore, we will use the following bivariate specification,

$$\begin{bmatrix} h_{11t} & h_{12t} \\ \cdot & h_{22t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ \cdot & c_{22} \end{bmatrix} \circ \begin{bmatrix} c_{11} & c_{12} \\ \cdot & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ \cdot & a_{22} \end{bmatrix} \circ \begin{bmatrix} sin(2\pi t/52) & sin(2\pi t/52) \\ \cdot & sin(2\pi t/52) \end{bmatrix}$$
$$+ \begin{bmatrix} b_{11} & b_{12} \\ \cdot & b_{22} \end{bmatrix} \circ \begin{bmatrix} cos(2\pi t/52) & cos(2\pi t/52) \\ \cdot & cos(2\pi t/52) \end{bmatrix} \tag{16}$$

where c_{ij}, a_{ij} and b_{ij} for all i, j = 1, 2 are parameters, t indicates week number within the year and ° is the Hadamard product operator (element-by-element matrix multiplication). We tried many other specifications and combinations, but this simple specification was the most powerful and did not present difficulties in the estimation procedure.

3.3 The seasonal-basis covariance model

Based on returns volatility and basis seasonality, we propose the following covariance model where the seasonal pattern in the conditional covariance is introduced using the sinusoidal function previously estimated for the basis:

$$B(t) = a + b\,sin(2\pi\, t/52) + c\,cos(2\pi\, t/52)$$

$$\begin{bmatrix} h_{11t} & h_{12t} \\ \cdot & h_{22t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ \cdot & c_{22} \end{bmatrix} \circ \begin{bmatrix} c_{11} & c_{12} \\ \cdot & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ \cdot & a_{22} \end{bmatrix} \circ \begin{bmatrix} \hat{B}(t-1) & \hat{B}(t-1) \\ \cdot & \hat{B}(t-1) \end{bmatrix} \quad (17)$$

where c_{ij}, and a_{ij} for all i, j = 1, 2 and a, b and c are parameters.

The parameters of the bivariate covariance models are estimated by maximizing the conditional log-likelihood function:

$$L(\theta) = -\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln\left|H_t(\theta)\right| + \varepsilon_t' H_t^{-1}(\theta)\varepsilon_t\right) \quad (18)$$

where T is the number of observations, N is the number of equations in the system, and θ denotes the vector of all the parameters to be estimated. The log likelihood function is estimated by using the BFGS algorithm via *quasi-maximum likelihood estimation* (QMLE). Bollerslev and Wooldridge (1992) show that the standard errors calculated by using this method are robust even when the normality assumption is violated.

4. Data and preliminary analysis

Natural gas spot and futures prices are directly obtained from Platts and the ICE, respectively. The spot price is computed and published daily for delivery next working day after assignment. This spot is the reference for derivative contracts traded at the ICE and those contracts traded OTC in the respective hub. There is a wide range of natural gas derivative contracts (forward, futures, and options) traded at the ICE. At the moment, the most important of the regulated contracts are monthly futures, especially the front month contract, the most liquid of all the traded contracts. The vast majority of contracts currently traded are OTC contracts, but futures contracts are becoming more important over time as markets become more liquid and more reliable.[9]

[9] “First to delivery futures contract”, “futures front contract” and “first to maturity futures contract” are used interchangeably for nearby futures contracts.

To select which futures/forward contracts can be included in this study two important considerations are necessary: (i) firstly, a large number of observations are required to obtain insightful results; (ii) secondly, non-overlapping futures contracts are preferable in order to avoid artificially introducing autocorrelation in the data series. Therefore, it is necessary to balance the data frequency and delivery period length of the contracts to avoid introducing autocorrelation in the data series. Following these premises, the present study has focused on short-time hedges using weekly frequency, the front futures contract, and long-time hedges of one, three, and six months using monthly frequency data for the first, third and sixth to maturity monthly futures contracts. We are confident that our results, estimates, and conclusions are unaffected by autocorrelation.

Futures and forwards contracts have coexisted from the beginning, but the majority of trades are through OTC contracts. Futures negotiated at the ICE are increasing their importance and liquidity over time and they represent more than one-third of all gas negotiated at NBP (Heather, 2010). The ICE trades monthly, quarterly, seasonal, and yearly futures contracts in the three markets (the monthly futures being the most liquid). To avoid low liquidity problems the study has been limited to the first six monthly contracts nearest to delivery and the corresponding spot. With this information four type of hedges are designed as described in Table 1. Three and six months hedges are only available for the UK market. The data period for the NBP market goes from December 3, 1997 until March 26, 2014; that is, 196 months or 852 weeks in the NBP. For the ZEE market the data sample goes from October 20, 1999 until March 26, 2014; that is, 174 months or 754 weeks. For the TTF market the data sample goes from January 7, 2004 until March 26, 2014; that is, 123 months or 534 weeks.

In the ICE, final futures settlement covers the difference between the last closing price of the futures contract and the system price in the ‘delivery period’. The day ahead price is used as spot price reference in the three markets. In monthly contracts, the spot reference is the spot average of all the calendar days of the month.

Figure 1 exhibits the time series for the spot and front contract in each market on a weekly frequency. Futures prices are taken on Wednesday, or the day before if non-tradable.[10] The most relevant jumps corresponds to events mostly related with geopolitics: the dispute between Russia and Ukraine about the price of gas and transit combined with abnormally cold weather (3 March 2005, 22 November 2005, January 2009, February 2012) and the Libyan civil war (spring 2011). But the most dramatic shortcoming and peak was during February and March 2006 when a cold spell was combined with a fire at the Rough natural gas storage facilities in the North Sea – preventing access to nearly over 80% of total UK storage just as withdrawals from storage were about to begin (see Giulietti et al., 2011).

A preliminary analysis follows. Table 2 displays the basic statistics of spot and futures price differences. Mean values deserve the first important comment. Whereas spot mean values are positive but not significantly different from zero, futures means are negative and significantly different from zero in all cases. Furthermore, the mean values of $\Delta^k F(t,T_i)$, take values varying between -0.31 (k=w) and -4.10 (k=6m) for the NBP. In the classical view of hedging pressure as a determinant of futures premiums (also known as a *forward bias* or *forward premium*) when a significant declining pattern is found in futures prices (futures prices above expected spot prices) it would be said that the futures market is in *contango* (long hedging pressure). The Kruskal-Wallis test contrasts the null of median equality between spot and futures time series. Results show that the null is rejected in all cases. The augmented Dickey and Fuller (1981) and Phillips and Perron (1988) unit root tests could not reject at the 5% significance level the null hypothesis of the existence of a unit root in all the spot and futures price time series. The Johansen (1988) tests for cointegration offered no doubt of cointegration between each pair of spot and futures time series within each market.

Table 2 also displays the standard deviation of the analyzed series. A pair-wise comparison between spot and futures standard deviation shows that the former is always higher. The Levene test

[10] Wednesday is the standard day in financial markets for weekly time series. Taking Wednesday prices avoids some of the anomalies (Monday effect and weekend effect) that are very common in financial markets. Chordia and Swaminathan (2000) find that return autocorrelations based on closing prices of any weekday other than Wednesday are either too low or too high.

contrasts the null of variance equality between spot and futures differenced series. Results show that the null is rejected in all markets at 5% of significance level for weekly returns but not for longer periods.

Significant skewness is found in 3 out the 16 time series analyzed in Table 2: one week futures and one month spot returns in the TTF and six month spot returns time series in the NBP. The kurtosis results indicate that all the time series appearing in Table 2 have significant excess kurtosis. In accordance with the above results, normality distribution hypothesis is clearly rejected in all cases. Maximum and minimum values help to explain the above results, especially the high kurtosis. Finally, the Ljung-Box test with twenty lags detects significant autocorrelation and heteroscedasticity.

The statistical behavior of futures and spot differences has some significant discrepancies that might be critical obstacles to overcome in order to design a successful hedging strategy. The two most insightful results are that futures have a declining pattern as maturity approaches, and that spot prices are more volatile than futures prices. This disparity produces a lower correlation than usual for linking futures and the spot position to hedge. This correlation appears in Table 3 and varies between 0.43 and 0.75. The highest correlation between spot and futures are obtained for one-month price variations and lowest values correspond to three and six months. This is an interesting point to keep in mind when considering the choice of the optimal hedging strategy. Nevertheless, later it will be shown that hedging effectiveness increases as the hedging period increases, then a hasty interpretation of the correlation coefficient in terms of choosing the best hedging alternative may be wrong. In this case, the strong seasonal pattern on prices and volatility makes it necessary to use unexpected price changes to avoid misunderstandings.

4.1 Seasonality in basis and volatility

Basis has a strong seasonal pattern when convenience yield, weather, and storage costs vary during the year (Whei and Zhu (2006)). Basis is positive in winter and negative in summer. In winter, demand is great and so storage levels decrease and storage costs increase (positive convenience yield), producing a positive basis. In summer, demand for natural gas is lower because of warm weather and storage prices decrease and storage levels increase (negative convenience yield) and the combination of these effects results in a negative basis. Basis and price volatility have a similar seasonal pattern, see Figures 2 and 3.

Basis and returns volatility are high in winter and low in summer. Furthermore, the basis contains information of those variables (storage levels, weather, demand, and risk premiums) that reflect uncertainty in the natural spot-futures markets necessary to obtain futures prices. Finally, in contrast to spot and price levels where jumps are frequently found, the basis is more stable as the liaison between spot and futures prices is constrained by the arbitrage arguments. The basis-seasonal model tries to cope and mix both seasonal effects in a covariance model, see equation (17).

Seasonal effects are further studied in Table 4. Using the weekly database, the year is divided in two seasons in the same way as the futures *seasonal contracts* in the ICE market: winter from October to March and summer from April to September. Results show that mean equality between basis, spot, and futures returns cannot be rejected. In contrast, the winter volatility of these variables is significantly higher than summer volatility.

In Table 5 some evidence of the predictive ability of the basis for the spot and futures price changes is presented. As this table shows, the basis has an important predictive power for explaining unexpected spot price changes (between 10% and 32%). However, the basis has less ability to forecast futures price changes. These results coincide with the Ederington and Salas (2008) approach where spot price changes are partially predictable; but futures prices results agree with the martingale hypothesis in most cases.

5. Results

The estimation of the conditional covariance models (see equations (13) to (17)) is carried out by maximizing the sample log-likelihood function (see equation (18)). The estimation outputs for the first five years used as ex post period in the three conditional covariance models are reported in Tables 6, 7 and 8. Looking at the results appearing in Panel (B) in all these tables, autocorrelation problems completely disappear. Nevertheless, heteroscedasticity is almost eliminated with the BEKK model but persists in seasonal models. Skewness and kurtosis statistics remain in similar values to the original data appearing in Table 2.

Figures 4 and 5 display, respectively, the estimated conditional second moment and hedging ratios.[11] It can be seen how second moments in Figure 4 have a very clear pattern model similar to the raw data appearing in Figure 3. That is, volatility increases in all winter seasons and there was a special period of high volatility beginning in the winter between 2005 and 2006. Furthermore, volatility is about twice as high in spot comparted to futures prices. Finally, the strength of the seasonal pattern appears to soften towards the end of the sample period.

In Figures 5(a) and 5(b) it can be seen how conditional hedging ratio values move around linear regression based hedge ratios. In all cases, average hedge values decrease from the beginning until the end of the sample. One interesting fact is to test if hedge ratios in summer and winter are equal in mean. In the *ex post* period, hedge ratios are significantly higher in summer for the BEKK, and significantly lower in summer in seasonal models; nevertheless, equality in mean cannot be rejected in the *ex ante* period in both cases at 5% of significance level.[12] These results can partially be related with Chang et al. (2010) results, who found that risk reduction in bull markets (low volatility) is higher than risk reduction in bear markets (high volatility) in oil markets. We have tested if risk reduction values change by seasons. In this case, we obtain similar results to those reported in Table 9 for both seasons. Consequently, as shown by the results of the *ex ante* period, the various hedging strategies offer no significant differences between seasons.

[11] Results for the seasonal model are not included in Figures 4 and 5 because they are very similar to the seasonal-basis model.

[12] We tested the mean equality between winter and summer hedges (H_0: $\mu_W = \mu_S$) using the following t-test with asymptotic normal distribution $t_{H_0} = (\mu_W - \mu_S) \Big/ \sqrt{\sigma_W^2 / n_W + \sigma_S^2 / n_S}$, been μ_W , μ_S , σ_S^2 , σ_W^2 , n_W and n_S the means, variances, and sample sizes of hedge values for winter and summer, respectively. In the BEKK model we obtained μ_W =1.79, μ_S =1.86 and t-statistic of -6.24 in the *ex post* period and μ_W =1.54, μ_S =1.54 and a t-statistic of 0.11 in the *ex ante* period. In the seasonal-basis model we obtained μ_W =1.77, μ_S =1.52 and a t-statistic of 29.32 in the *ex post* period and μ_W =1.50, μ_S =1.47 and t-statistic of 1.51 in the *ex ante* period.

Table 9 and 10 display the variance reduction of the different hedging methods.[13] In Table 9 risk reduction corresponding to weekly hedges in NBP, ZEE, and TTF are reported in panels A, B, and C. The first important result is that in all cases the risk reduction in the standard approach is underestimated by more than a 10%. In the *ex post* periods the naïve hedge is the worst performing strategy and the other strategy obtains similar results. Anyway, the only realistic comparison can be made in the *ex ante* period where hedge strategies are compared using forecasted hedge ratios, and models are estimated every time a new observation is considered. In this case, for the NBP and ZEE markets the seasonal-basis strategy produces the largest risk reduction (46.81% and 44.44%, respectively), somewhat larger than the risk reduction obtained using the OLS and seasonal strategies. The BEKK and the naïve strategies produce the worst outcomes. In the TTF market in Panel (C) the naïve hedge obtains first position (46.46%), followed with a slightly lower risk reduction by "OLS w/o basis" and seasonal-basis strategies. The BEKK method produces the poorest result. It is interesting to note that obtaining risk reductions below 50% is quite common when futures hedging is carried out on commodities and the standard approach is used (Carter, 1999; section 3.2).[14]

In Table 10 results corresponding 1, 3 and 6 months hedging periods are displayed. In this case, the underestimation of the risk reduction using the standard approach is critical. In the *ex ante* period the difference between these two risk reduction methods varies between 40 percent and more than the 100 percent. Particularly noteworthy is the case of the NBP in the *ex ante* period where the standard approach offers a risk increase (negative risk reduction) in many cases. Proposition 3 in Ederington and Salas (2008) can be used to explain the "negatives" as this proposition says that the

[13] Transaction costs are not considered when comparing hedging methods, as the hedging theoretical framework is a one-period model for all hedging methods. Within this framework, the individual (see Section 2) must take futures positions at the beginning of the period and cancel them at the end of the period. As hedging ratio values are quite similar in all the considered methods, all the hedging strategies will have similar transaction costs. Extracted from ICE rules in May 2014, the total member trading fees for a contract will be £1.90 and €2.70 for NBP and TTF monthly contracts, respectively (about 0.003% and 0.02% of the underlying value in each case). Following Wagner (2014), the bid-ask average spreads in the most liquid European natural gas futures contracts are about 0.001£ for NBP and ZEE and 0.1€ for the TTF. These quantities respectively represent about 0.25% and 0.5% of the total underlying amount.

[14] Although not directly displayed in Tables 9 and 10 it is important to note that the Newey-West standard errors of the hedge ratios estimated using equation (8) are 50% lower on average than those obtained after using equation (4). Consequently, the introduction of the basis in the model allows more efficient minimum variance hedge ratio estimates.

exclusion of the basis (expected price changes) in the computation of the spot position risk to hedge tends to overestimate the variance of the spot position variance by the variance of the basis (proxy of the expected spot price changes). Looking at Table 11 it can be seen that in the *ex ante* period the basis variance is very high compared with the spot return variance and it is higher in one case. When the basis has such a great a variance, the standard approach can then report a misleading risk increase because risk reduction is dramatically underestimated.

The attained risk reduction of naïve and OLS based hedges shown in Table 10 are quite similar in all the cases in the E&S(2008) approach and vary between 79% and 93% in the *ex ante* period. The naïve strategy obtains the greatest risk reduction in three out of five cases and the "OLS w/o basis" in the remaining two cases in the *ex ante* period. In the *ex post* period the "OLS with basis" wins in four out of five cases. In all cases, we detected a positive duration effect in hedging effectiveness. The achieved risk reduction is larger in one month than in the one week hedging period. Furthermore, in the NBP case where 3 and 6 month hedges are carried out, the risk reduction obtained by the optimal hedging strategy further increases with the duration of the hedge. The level of risk reduction reached in ZEE and TTF markets for 1 month hedges is remarkable. In this case, risk reduction is very successful and it is almost as high as the 6 month hedges in the NBP. This result is interesting for futures traders, who design hedging strategies, as it shows that trading with the front contract in the ZEE and TTF is very successful and furthermore, the front contract is always the more liquid contract and allows tailing and steering the futures positions dynamically with low trading costs.

Differences in risk reduction obtained by OLS methods (with and without the basis) are inconclusive. Nevertheless, in Figure 5 where OLS weekly hedge ratios for the NBP are displayed, "OLS with basis" hedge ratios are above "OLS w/o basis". In ZEE and TTF week hedges we obtain a similar pattern. We find the reverse result for longer hedging periods: "OLS w/o basis" hedge ratios are above "OLS with basis". Ederington and Salas (2008) have shown that when spot price returns can be partially forecasted, then more efficient estimates can be obtained using their approach. However, our approach shows that a more efficient hedge ratio estimate will not imply an improvement in the performance of the hedging strategy. Finally, when OLS and GARCH hedge ratio performances are compared, results favor OLS hedge ratios. This finding implies that the better statistical performance of the GARCH models does not lead to better hedging strategy performance. This is not surprising given the hedging literature, and according to Lien and Tse's (2002, page 367) review: empirical results concerning the performance of GARCH hedge ratios are generally mixed and conventional hedge strategies perform as well as or better than the GARCH strategies. Furthermore, the naive strategy leads to a similar performance to the remaining strategies in long-term hedges and it is the best performing strategy for weekly hedges in the case of the TTF market. We also explore how hedging strategies deal with spikes in spot prices. We compute two specific risk measures specially suitable for examining how optimal variance hedging strategies are dealing with spikes in spot prices: the *value at risk* (*VaR*) and the *expected shortfall* (*ES*). The $VaR(\alpha)$ can be interpreted as the cut-off point where the probability that a larger loss (or profit) in the expected hedged portfolio will not happen with a probability greater than α percent. Results are computed for α=1% and α=99% because the negative and positive tails are of interest for long and short positions in the spot market, respectively. We used the observed data frequencies to compute these cut-off points. The *ES* is the expected value of the loss when these cut-off points are exceeded and is computed as the mean value of those hedging portfolio results contained in each tail. See Jorion (2003) for more details. The results reported at table 12, show that spikes are greatly reduced when spot positions are hedged. It is important to highlight that the cut-off values of these statistics are further reduced as hedge duration increases. These reductions have a similar pattern to the hedging effectiveness in Tables 9 and 10, as the effectiveness of the hedge significantly improves with the duration of the hedge. The cut-off statistic interval lengths are progressively reduced from about 25%, 50%, or even 75% as hedge duration progressively increases from one week to six months.

Finally, in order to test the statistical significance variance risk reductions for each pair of hedging strategies, White's reality check was performed (see Section 2) on the *out of sample* period for each pair of strategies in each panel in Tables 9 and 10. The no improvement null hypothesis of a better performing strategy for each possible pair of compared strategies is rejected in all cases. Specifically, the *p*-values in Table 9 and 10 are all below 5% and 1%, respectively. Consequently we can conclude that hedging performance differences are statistically significant in all cases.

6. Conclusions

This paper follows the Ederington and Salas (2008) framework considering the expected change in spot prices when minimum variance hedge ratios are computed. The use of this new approach enables a significant improvement on the effectiveness measures for hedging strategies obtained in some previous studies on energy markets (see Bystrom, 2003 and Moulton 2005 for electricity, and Ederington and Salas (2008) for the US natural gas market). Specifically, previous studies have overestimated the unexpected shocks in spot prices as a large part of these shocks (between 10% and 30%) can be partially anticipated using the information contained in the basis. Consequently, the riskiness of the spot position in previous studies was overestimated and the achievable risk reduction underestimated. This poor effectiveness was also due to the special statistical features of most energy commodity prices. The special statistical features of natural gas prices (specifically their high volatility, kurtosis, seasonality and the high volatility of the basis) can produce very wrong computed risk reductions that can be corrected using the Ederington and Salas (2008) framework (in which past values of the basis are used to anticipate the seasonal trend of the spot price return).

Further to the use of the approach proposed by Ederington and Salas (2008), the empirical study carried out reveals that hedging performance can be significantly improved by increasing hedging duration. Depending on the hedging duration (one week, or one, three, and six months), and the analyzed sub-period (in-sample and out-of-sample sub-periods), risk reduction attains values of between 44% and 93%.

A strong seasonality also exists in the volatility of spot and futures price returns – which have been significantly higher in winter than in summer. We have captured this seasonality introducing a sinusoidal trend in conditional second moments. This is the first paper, to our knowledge, dealing with the influence of energy variance seasonality on MV hedging ratios and its effectiveness. Seasonalities in second moments are transmitted to the hedging ratios in the *ex post* period, been higher in winter than in summer. Nevertheless, in the more realistic *ex ante* processing, this difference is not statistically significant. A simple volatility seasonal based model built fitting sinusoidal functions on the basis (futures price less spot price) improves the risk reduction obtained by those strategies in which hedging ratios are estimated with linear regressions. Seasonal hedging strategies, linear regression based strategies, or even a naïve position prove to perform better than more sophisticated statistical methods. Consequently, it does not seem that improving statistical price modeling in natural gas markets guarantees a better hedging performance.

References

Alexander C., Prokopczuk M., and Sumawong A. (2013) The (de)merits of minimum-variance hedging: Application to crack spread. Energy Economics 36, 698-707.

Alterman, S. (2012) Natural gas price volatility in the UK and North America. Oxford Institute for Energy Studies.

Baillie, R. T., and Myers, R. J. (1991) Bivariate GARCH estimation of the optimal commodity futures hedge. Journal of Applied Econometrics, 6, 109-24.

Bekaert, G., & Wu, G. (2000). Asymmetric volatility and risk in equity markets. The Review of Financial Studies, 13, 1-42.

Benth, F. E., and Benth, J. S. (2007) The volatility of temperature and pricing of weather derivatives. Quantitative Finance, 7(5), 553-561.

Bollerslev, T. (1990). Modeling the coherence in short-run nominal rates: a multivariate generalized ARCH approach. Review of Economics and Statistics, 72, 498-505.

Bollerslev, T., & Wooldrige, J. M. (1992). Quasi-maximum likelihood estimation and inference in models with time varying covariances. Econometric Review, 11, 143-72.

Bollerslev, T., Engle R. F., & Wooldrige, J. M. (1988). A capital asset pricing model with time varying covariances. Journal of Political Economy, 96, 116-31.

Bystrom, H. N. (2003). The hedging performance of electricity futures on the Nordic power exchange. Applied Economics, 35, 1-11.

Carter, C. A. (1999). Commodity futures markets: a survey. The Australian Journal of Agricultural and Resource Economics, 43, 209-47.

Cecchetti, S. G., Cumby, R. E., & Figlewski, S. (1988). Estimation of the optimal futures hedge. Review of Economics and Statistics, 70, 623-30.

Chang, C. Y., Lai, J. Y., and Chuang, I. Y. (2010). Futures Hedging Effectiveness under segmentation of bear/bull energy markets. Energy Economics 32, 442-449.

Chordia, T., and B. Swaminathan (2000). Trading volume and cross-autocorrelations in stock returns. Journal of Finance 55, 913–935.

Cotter, J., and Hanly J. (2010) Time-varying risk aversion: an application to energy hedging. Energy Economics 32, 432-441.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root'. Econometrica, 49, 1057–72.

Ederington, L. H. (1979). The hedging performance of the new futures markets. Journal of Finance, 34, 157-170.

Ederington, L. H., & Salas, J. M. (2008). Minimum variance hedging when spot price changes are partially predictable. Journal of Banking and Finance, 32, 654-663.

Efimova, O., and Serletis, A. (2014) Energy Markets Volatility Modelling using GARCH. Energy Economics, forthcoming.

Engle, R. F., & Granger, C. W. (1987). Cointegration and error correction: representation, estimation and testing. Econometrica, 55, 251-76.

Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. Econometric Theory, 11, 122-50.

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatilily. The Journal of Finance, 48, 1749 – 78.

Fama, E. F., and French, K. R. (1987). Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage. Journal of Business, 60, 55-74.

Gagnon, L., & Lypny, G. (1995). Hedging short-term interest risk under time-varying distributions. The Journal of Futures Markets, 15, 767-783.

Giulietti, M., Grossi, L., and Waterson, M. (2011) A Rough Examination of the value of gas storage. Warwick Economic Research Papers No 967, Department of Economics, University of Warwick.

Glosten, L. R., Jagannathan, R., & Runkel, D. E. (1993). On the relation between the expected value and volatility of nominal excess return on stocks. The Journal of Finance, 48, 1779-801.

Hannan, E. J., and B. G. Quinn (1979). The determination of the order of an autoregression. Journal of the Royal Statistical Society B 41, 190–195.

Heather, P. (2010) The evolution and functioning of the traded gas market in Britain. Oxford Institute for Energy Studies, NG 44.

Heather, P. (2012). Continental European Gas Hubs: Are they fit for purpose? Oxford Institute for Energy Studies, NG 63.

Henaff, P., Laachir, I., and Russo, F. (2013) Gas storage valuation and hedging. A quantification of the model risk. Working paper. ArXiv:1312.3789v1[q-fin.PR] 13 Dec 2013.

Hendry, O. L., and Sharma, J. (1999). Asymmetric conditional volatility and firm size: evidence from Australian equity portfolios. Australian Economic Papers, 38, 393-406.

International Energy Agency (2013). Medium-Term Gas Market Report 2013 - Market Trends and Projections to 2018.

Johansen, S. (1988). Statistical analysis of cointegration vectors'. Journal of Economic Dynamics and Control, 12, 231–54.

Jorion, P. (2003). Financial Risk Manager Handbook. Second Edition. John Wiley & Sons, Inc. Hoboken, New Jersey.

Kao, C.W., and Wan, J.Y. (2009) Information transmission and market interactions across the Atlantic – an empirical study on the natural gas market. Energy Economics 31, 152-161.

Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. The Review of Financial Studies, 11, 817-44.

Kroner, K. F., & Sultan J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. Journal of Financial and Quantitative Analysis, 28, 535-51.

Lee, H. T., & Yoder, J. K. (2007a). Optimal hedging with a regime-switching timevariance correlation GARCH model. The Journal of Futures Markets, 27, 495-516.

Lee, H. T., & Yoder, J. K. (2007b). A bivariate Markov regime switching GARCH approach to estimate time varying minimum variance hedge ratio. Applied Economics, 39, 1253-65.

Lien, D. (1996). The Effect of the Cointegration Relationship on Futures Hedging: A Note. The Journal of Futures Markets, 16, 773-780.

Lien, D., & Tse, Y. K. (2002). Some recent developments in futures hedging. Journal of Economic Surveys, 16, 357-96.

Lindahl, M. (1992). Minimum variance hedge ratios for stocks index futures: duration and expiration effects. The Journal of Futures Markets, 12, 403-13.

MacKinnon, J.G. (1996) Numerical distribution functions for unit root and cointegration tests. Journal of applied econometrics, 11, 601-18.

MacKinnon, J.G., Haug, A., & Michelis, L. (1999) Numerical Distribution Functions of Likelihood Ratio Tests for Cointegration. Journal of Applied Econometrics, 14, 563-77.

Moulton, J. S. (2005). California electricity futures: The NYMEX experience. Energy Economics, 27, 181-94.

Mu, X. (2007) Weather, storage and natural gas price dynamics: Fundamentals and volatility.

Energy Economics 29, 46-63

Myers, R. J. (1991). Estimating time-varying optimal hedge ratios on futures markets. The Journal of Futures Markets, 11, 39-53.

Park, T. H., & Switzer, L. N. (1995). Bivariate GARCH estimation of the optimal hedge ratios for stock index futures: a note. The Journal of Futures Markets, 15, 61-7.

Phillips, P. C. B., & Perron, P. (1988) Testing for a unit root in time series regression. Biometrika, 75, 335–46.

Politis, D., & Romano, J. P. (1994). The stationary bootstrap. Journal of the American Statistical Association, 89, 1303-13.

Suenaga, H., Smith, A., and Williams J. (2008) Volatility dynamics of NYMEX natural gas futures prices. The Journal of Futures Markets 28, 438-463.

Viswanath, P.V. (1993). Efficient use of information, convergence adjustments, and regression estimates of hedges ratios. The Journal of Futures Markets, 13, 43-53.

Wagner, A. (2014). Functioning of European gas wholesale markets. 3rd Gas target model stakeholders workshop. Agency for the Cooperation of Energy Regulators. Brussels, 15th May.

Wei, S.Z.C. and Zhu, Z. (2006) Commodity convenience yield and risk premium: The case of US natural gas market. Energy Economics 28, 523-534.

White, H. (2000). A reality check for data snooping. Econometrica, 68, 1097-1126.

Annex I: tables

Table 1. Type of hedges

This table displays the type of hedges and helps clarify notation. Spot returns are computed as $\Delta^k S(t) = S(t+k)$-$S(t)$ with k = 1 week and 1, 3, and 6 months; and represent the NBP price variation for the k period. $\Delta^k F(t,T_i) = F(t+k,T_i)$-$F(t,T_i)$ with $T_i = t+i$; i = 1, 3, and 6 months and $k \leq i$. Note that prices are taken on Wednesday (previous trading day is used if not tradable) and futures rollovers are taken the last Wednesday of the month (or second to last Wednesday of the month if the last trading day of the month is Wednesday). Note that $F(t+k,T_i) \neq S(t+k)$ when $k = i$, as this is not a direct hedge. 'Duration' column reports the hedging period. The last column reports the basis used to approximate the expected spot price change in equation (8).

Duration k	Frequency	Spot return $\Delta^k S(t)$	Futures return $\Delta^k F(t,T_i)$	Basis approximating $E\left[\Delta^k S(t) \mid \psi_t\right]$
1 week	weekly	$\Delta^w S(t) = S(t+1\text{ week}) - S(t)$	$\Delta^w F(t,T_1) = F(\text{t+1week},T_1)\text{-}F(t,T_1))$	$F(t,T_1)\text{-}S(t)$
1 month	monthly	$\Delta^{1m} S(t) = S(t+1\text{ month}) - S(t)$	$\Delta^{1m} F(t,T_1) = F(\text{t+1month},T_1)\text{-}F(t,T_1))$	$F(t,T_1)\text{-}S(t)$
3 month	monthly	$\Delta^{3m} S(t) = S(t+3\text{ months}) - S(t)$	$\Delta^{3m} F(t,T_3) = F(\text{t+3months},T_3)/F(t,T_3))$	$F(t,T_3)\text{-}S(t)$
6 month	monthly	$\Delta^{6m} S(t) = S(t+6\text{ months})\text{- } S(t))$	$\Delta^{6m} F(t,T_6) = F(\text{t+6months},T_6)\text{-}F(t,T_6))$	$F(t,T_6)\text{-}S(t)$

Table 2. Summary statistics of spot and futures prices returns

The variables appearing in the heading of each column are described in Table 1. The *Kruskal-Wallis* and *Levene* statistics test median and variance equality, respectively, between $\Delta^k S(t)$ and $\Delta^k F(t,T_i)$. *Skewness* means the skewness coefficient and has the asymptotic distribution N(0,6/T) under normality, where T is the sample size. The null hypothesis tests whether the skewness coefficient is equal to zero. *Kurtosis* means the excess kurtosis coefficient and it has an asymptotic distribution of N(0,24/T) under normality. The hypothesis tests whether the kurtosis coefficient is equal to zero. The *Jarque-Bera* statistic tests for the normal distribution hypothesis. The Jarque-Bera statistic is calculated as T[*Skewness*^{2}/6+(*Kurtosis*)^2/24]. The Jarque-Bera statistic has an asymptotic $\chi^2(2)$ distribution under the normal distribution hypothesis. *Q(20)* and *Q^2(20)* are Ljung Box tests for twentieth order serial correlation in the differentiated and its squared series, respectively. Marginal significance levels of the statistical tests are displayed as [.].

Panel (A): One week variations

	NBP				ZEE				TTF			
	$\Delta^w S(t)$		$\Delta^w F(t,T_1)$		$\Delta^w S(t)$		$\Delta^w F(t,T_1)$		$\Delta^w S(t)$		$\Delta^w F(t,T_1)$	
Mean	0.04	[0.83]	–0.31	[0.00]	0.05	[0.80]	–0.27	[0.00]	0.02	[0.83]	–0.15	[0.00]
Median	0.02		–0.19		0.1		–0.22		0.00		–0.10	
Kruskal-Wallis			9.98	[0.00]			7.75	[0.00]			7.91	[0.00]
S. D.	5.94		2.56		6.36		2.63		2.10		0.98	
Levene			78.31	[0.00]			49.82	[0.00]			36.16	[0.00]
Skewness	0.46	[0.00]	1.17	[0.00]	0.37	[0.00]	1.09	[0.00]	–0.41	[0.00]	-0.10	[0.33]
Kurtosis	28.66	[0.00]	19.90	[0.00]	47.91	[0.00]	16.97	[0.00]	25.89	[0.00]	6.20	[0.00]
Jarque-Bera	2.8×10^3	[0.00]	1.4×10^5	[0.00]	7.1×10^4	[0.00]	9.1×10^3	[0.00]	1.1×10^4	[0.00]	228.78	[0.00]
Maximum	55		25.23		67.25		24.32		17.35		4.55	
Minimum	-55		-17.45		–70.05		–16.45		–16.75		–4.55	
Q(20)	302.73	[0.00]	412.77	[0.00]	314.87	[0.00]	416.29	[0.00]	149.44	[0.00]	169.52	[0.00]
Q^2(20)	260.75	[0.00]	622.43	[0.00]	229.84	[0.00]	555.68	[0.00]	70.98	[0.00]	189.16	[0.00]

Table 2 (continued). Summary statistics of spot and futures prices returns

Panel (B): One month variations

	NBP				ZEE				TTF			
	$\Delta^{1m} S(t)$		$\Delta^{1m} F(t,T_1)$		$\Delta^{1m} S(t)$		$\Delta^{1m} F(t,T_1)$		$\Delta^{1m} S(t)$		$\Delta^{1m} F(t,T_1)$	
Mean	0.22	[0.78]	–1.36	[0.00]	0.23	[0.74]	-1.15	[0.02]	0.07	[0.82]	-0.68	[0.00]
Median	0.10		–0.66		0.22		-0.80		-0.12		-0.45	
Kruskal-Wallis			7.08	[0.00]			5.01	[0.02]			3.55	[0.06]
S. D.	10.98		5.99		9.33		6.39		3.41		2.53	
Levene			3.29	[0.07]			3.54	[0.06]			2.30	[0.13]
Skewness	2.80	[0.00]	0.36	[0.04]	2.00	[0.00]	1.07	[0.00]	0.12	[0.59]	-0.75	[0.00]
Kurtosis	40.59	[0.00]	11.39	[0.00]	22.46	[0.00]	16.78	[0.00]	4.85	[0.00]	1.88	[0.00]
Jarque-Bera	1.3×10^4	[0.00]	1.1×10^3	[0.00]	3.5×10^3	[0.00]	3.5×10^3	[0.00]	1.1×10^3	[0.00]	27.15	[0.00]
Maximum	100.55		38.01		72.05		44.37		13.27		5.47	
Minimum	-59.5		-27.20		-33.57		-28.90		-12.40		-9.95	
Q(20)	99.357	[0.00]	79.74	[0.00]	102.86	[0.00]	63.28	[0.00]	68.63	[0.00]	54.91	[0.00]
Q^2(20)	36.09	[0.01]	40.82	[0.00]	43.015	[0.00]	29.764	[0.07]	28.69	[0.09]	47.83	[0.00]

Panel (C): Three and six months returns

	NBP				NBP			
	$\Delta^{3m} S(t)$		$\Delta^{3m} F(t,T_3)$		$\Delta^{6m} S(t)$		$\Delta^{6m} F(t,T_6)$	
Mean	0.72	[0.46]	–3.22	[0.00]	1.67	[0.19]	–4.10	[0.00]
Median	0.72		–1.38		2.00		1.30	
Kruskal-Wallis			14.78	[0.00]			16.72	[0.00]
S. D.	13.75		10.25		17.53		14.24	
Levene			1.29	[0.25]			1.22	[0.27]
Skewness	1.68	[0.00]	-1.40	[0.00]	-0.06	[0.71]	-1.96	[0.00]
Kurtosis	17.80	[0.00]	5.70	[0.00]	12.22	[0.00]	5.62	[0.00]
Jarque-Bera	2499.5	[0.00]	308.1	[0.00]	1.1×10^3	[0.00]	371.89	[0.00]
Maximum	103.25		37.12		106.22		32.83	
Minimum	-53.6		-50.78		-98.75		-69.98	
Q(20)	74.97	[0.00]	36.34	[0.00]	305.39	[0.00]	603.17	[0.00]
Q^2(20)	72.31	[0.00]	34.35	[0.02]	76.016	[0.00]	229.15	[0.00]

Table 2 (continued). Summary statistics of spot and futures prices returns

Panel (A): One week variations

	NBP				ZEE				TTF			
	$S(t)$		$F(t,T_1)$		$S(t)$		$F(t,T_1)$		$S(t)$		$F(t,T_1)$	
ADF	-1.42	[0.15]	–0.89	[0.33]	-0.85	[0.35]	-0.69	[0.42]	-0.71	[0.41]	-0.45	[0.52]
PP	-1.23	[0.20]	–0.93	[0.32]	-1.10	[0.25]	-0.73	[0.40]	-0.60	[0.46]	-0.46	[0.51]

Panel (B): One month variations

ADF	-0.69	[0.42]	–0.77	[0.38]	-0.81	[0.36]	-0.81	[0.36]	-0.48	[0.50]	-0.43	[0.53]
PP	-0.99	[0.29]	–0.76	[0.38]	-0.87	[0.34]	-0.75	[0.39]	-0.63	[0.44]	-0.40	[0.54]

Panel (C): Three and six month returns

	NBP			
	$F(t,T_3)$		$F(t,T_6)$	
ADF	–1.20	[0.21]	-0.42	[0.53]
PP	–0.97	[0.30]	-1.08	[0.25]

ADF and PP refer to the augmented Dickey and Fuller (1981) and Phillips and Perron (1988) unit root tests in the time series. One-sided p-values computed following Mackinnon (1996) for the ADF and PP tests are displayed as [.] (corresponding to the process without intercept and without trend). The number of lags in the ADF test and the truncation lag in the PP test were obtained using information criteria (Schwarz and Newey and West, respectively). Marginal significance levels are displayed as [_] in the remaining tests.

Table 2 (continued). Johansen (1988) test for cointegration

Panel (A): One week frequency time series

		Lags	Null	λ_{trace} (r)	Critical value	λ_{max} (r)	Critical value
NBP	[$S(t)$, $F(t,T_1)$]	7	r=0	94.12114	20.26184	87.68546	15.89210
			r=1	6.435687	9.164546	6.435687	9.164546
TTF	[$S(t)$, $F(t,T_1)$]	1	r=0	100.1268	20.26184	93.98267	15.89210
			r=1	6.144084	9.164546	6.144084	9.164546
ZEE	[$S(t)$, $F(t,T_1)$]	7	r=0	85.39327	20.26184	78.44248	15.89210
			r=1	6.950793	9.164546	6.950793	9.164546

Panel (B): One month, three and six months frequency time series

		Lags	Null	λ_{trace} (r)	Critical value	λ_{max} (r)	Critical value
NBP	[$S(t)$, $F(t,T_1)$]	1	r=0	85.84689	20.26184	80.23231	15.89210
			r=1	5.614572	9.164546	5.614572	9.164546
	[$S(t)$, $F(t,T_3)$]	2	r=0	58.49014	20.26184	53.71355	15.89210
			r=1	4.776596	9.164546	4.776596	9.164546
	[$S(t)$, $F(t,T_6)$]	7	r=0	29.24686	20.26184	23.81799	15.89210
			r=1	5.428878	9.164546	5.428878	9.164546
TTF	[$S(t)$, $F(t,T_1)$]	1	r=0	50.09496	20.26184	43.77043	15.89210
			r=1	6.324522	9.164546	6.324522	9.164546
ZEE	[$S(t)$, $F(t,T_1)$]	1	r=0	77.06514	20.26184	70.13489	15.89210
			r=1	6.930249	9.164546	6.930249	9.164546

Note: The lag length is determined using the Hannan-Quinn Criteria. λ_{trace} (r) tests the null hypothesis that there are at most r cointegration relationships against the alternative that the number of cointegration vectors is greater than r. λ_{max} (r) tests the null hypothesis that there are r cointegration relationships against the alternative that the number of cointegration vectors is greater than r + 1. Critical values are from MacKinnon-Haug-Michelis (1999)).

Table 3. Correlation matrix of the spot and futures prices variations

The variables appearing in the heading of each row and columns are described in Table 1. For a sample size of T observations, the asymptotic distribution of the $\sqrt{T}$ times the correlation coefficient is a zero-one normal distribution. * indicates significance at the 1% significance level. TTF returns are converted to pence per therm dividing by (100×34.121415×€/£) been €/£ the exchange rate euro per pound sterling.

Panel (A). One-week

		NBP		ZEE		TTF	
		$\Delta^{w}S(t)$	$\Delta^{w}F(t,T_1)$	$\Delta^{w}S(t)$	$\Delta^{w}F(t,T_1)$	$\Delta^{w}S(t)$	$\Delta^{w}F(t,T_1)$
NBP	$\Delta^{w}S(t)$	1.0					
	$\Delta^{w}F(t,T_1)$	0.58*	1.0				
ZEE	$\Delta^{w}S(t)$	0.94*	0.56*	1.0			
	$\Delta^{w}F(t,T_1)$	0.59*	0.98*	0.56*	1.0		
TTF	$\Delta^{w}S(t)$	0.71*	0.45*	0.75*	0.45*	1.0	
	$\Delta^{w}F(t,T_1)$	0.33*	0.65*	0.32*	0.65*	0.59*	1.0

Panel (B). One-month

		NBP		ZEE		TTF	
		$\Delta^{1m}S(t)$	$\Delta^{1m}F(t,T_1)$	$\Delta^{1m}S(t)$	$\Delta^{1m}F(t,T_1)$	$\Delta^{1m}S(t)$	$\Delta^{1m}F(t,T_1)$
NBP	$\Delta^{1m}S(t)$	1.0					
	$\Delta^{1m}F(t,T_1)$	0.63*	1.0				
ZEE	$\Delta^{1m}S(t)$	0.92*	0.64*	1.0			
	$\Delta^{1m}F(t,T_1)$	0.70*	0.92*	0.75*	1.0		
TTF	$\Delta^{1m}S(t)$	0.67*	0.50*	0.79*	0.62*	1.0	
	$\Delta^{1m}F(t,T_1)$	0.39*	0.72*	0.47*	0.75*	0.71*	1.0

Panel (C). Three-month

	NBP	
	$\Delta^{3m}S(t)$	$\Delta^{3m}F(t,T_3)$
$\Delta^{3m}S(t)$	1.0	0.45*
$\Delta^{3m}F(t,T_3)$		1.0

Panel (D). Six-month

	NBP	
	$\Delta^{6m}S(t)$	$\Delta^{6m}F(t,T_6)$
$\Delta^{6m}S(t)$	1.0	0.43*
$\Delta^{6m}F(t,T_6)$		1.0

Table 4. Summer and winter mean and volatility

This table reports the weekly mean and volatility (standard deviation) of basis, spot, and futures returns in winter (October to March) and summer (April to September). *p-values* of the *Kruskal-Wallis* and *Levene* statistics test for median and variance equality, respectively, are reported.

	Summer Mean	Winter Mean	Equality Test	Summer Volatility	Winter Volatility	Equality Test
$F(t,T_1)$-$S(t)$						
NBP	1.26	1.16	0.19	4.34	8.40	0.00
ZEE	0.40	0.56	0.33	3.97	8.29	0.00
TTF	0.54	0.53	0.31	1.68	3.13	0.00
$\Delta^w S(t)$						
NBP	-0.04	0.12	0.93	3.14	7.74	0.00
ZEE	0.01	0.11	0.98	3.04	8.37	0.00
TTF	0.01	0.03	0.76	2.71	1.20	0.00
$\Delta^w F(t,T_1)$						
NBP	-0.18	-0.44	0.01	1.61	3.22	0.00
ZEE	-0.16	-0.38	0.12	1.70	3.28	0.00
TTF	-0.06	-0.25	0.04	0.77	1.14	0.00

Table 5. The basis as a predictor of the change in spot and futures prices

This table displays the results of the regression between spot and futures changes appearing in the first column on the basis as defined in the second column for the whole sample period. Between brackets *t*-statistic values computed with Newey-West standard errors are reported. Significant coefficients at the 1%, 5%, and 10% of significance level are highlighted with one (*), two (**) and three (***) asterisks, respectively.

			Panel (A). Week returns		
	Dependent variable	basis	Intercept	Basis coefficient	Adjusted R^2
NBP	$\Delta^{w} S(t)$	$F(t,T_1)$-$S(t)$	–0.33 (–1.85) ***	0.31 (4.93)*	11.88%
	$\Delta^{w} F(t,T_1)$	$F(t,T_1)$-$S(t)$	–0.23 (–2.69) *	–0.07(–3.41)*	3.09%
ZEE	$\Delta^{w} S(t)$	$F(t,T_1)$-$S(t)$	–0.34 (–1.67) ***	0.36 (3.99)*	14.03%
	$\Delta^{w} F(t,T_1)$	$F(t,T_1)$-$S(t)$	–0.21 (–2.19) **	–0.06(–2.32)**	2.38%
TTF	$\Delta^{w} S(t)$	$F(t,T_1)$-$S(t)$	–0.13 (–1.53)	0.26 (3.51)*	9.79%
	$\Delta^{w} F(t,T_1)$	$F(t,T_1)$-$S(t)$	–0.10 (–2.29) **	–0.09(–4.11)*	5.08%
			Panel (B). One-month returns		
NBP	$\Delta^{1m} S(t)$	$F(t,T_1)$-$S(t)$	–1.22 (–2.16)**	0.78 (2.76)*	30.93%
	$\Delta^{1m} F(t,T_1)$	$F(t,T_1)$-$S(t)$	–1.09 (–2.51)**	–0.34 (–0.83)	3.61%
ZEE	$\Delta^{1m} S(t)$	$F(t,T_1)$-$S(t)$	–1.00 (–1.86)	0.73 (3.25)*	24.39%
	$\Delta^{1m} F(t,T_1)$	$F(t,T_1)$-$S(t)$	–0.98 (–2.09)**	–0.09 (–0.49)	0.93%
TTF	$\Delta^{1m} S(t)$	$F(t,T_1)$-$S(t)$	–0.40 (–1.62)	0.51 (2.93)*	16.48%
	$\Delta^{1m} F(t,T_1)$	$F(t,T_1)$-$S(t)$	–0.38 (–1.73)***	–0.33 (–2.55)**	12.19%
			Panel (C). Three month returns		
NBP	$\Delta^{3m} S(t)$	$F(t,T_3)$-$S(t)$	–1.84 (–1.68)***	0.60 (3.08)*	31.48%
	$\Delta^{3m} F(t,T_3)$	$F(t,T_3)$-$S(t)$	–0.34 (–1.83)***	–0.33 (–1.83)***	1.80%
			Panel (C). Six month returns		
NBP	$\Delta^{6m} S(t)$	$F(t,T_6)$-$S(t)$	–1.89 (–1.07)	–0.40(3.00)*	31.55%
	$\Delta^{6m} F(t,T_6)$	$F(t,T_6)$-$S(t)$	–1.67 (–0.98)	–0.40(–2.22)**	22.27%

Table 6. BEKK model estimates

Using the pair of variables $\Delta^w S(t)$ $\Delta^w F(t,T_1)$ as described in Table 1 a VECM model as described in equation (13) is estimated. From each VECM, an innovation vector $(\varepsilon_{1t}, \varepsilon_{2t})'$ is obtained without autocorrelation problems. Panel (A) of this table displays the quasi maximum likelihood estimates of the BEKK model in equation (15) for the *ex post* sample. Panel (B) reports some statistics for the standardized residuals: *Skewness* coefficient has the asymptotic distribution N(0,6/T), where T is the sample size. The null hypothesis tested is that the standardized residual skewness coefficient is equal to zero. The excess *Kurtosis* coefficient has an asymptotic distribution of N(0,24/T). The hypothesis tested is that standardized residual kurtosis coefficient is equal to zero. *Q(20)* and *Q^2(20)* are Ljung Box tests for twentieth order serial correlation in the standardized residuals and its squared value; these two statistics are distributed as χ^2(20) under the null hypothesis of no autocorrelation. Significant coefficients or rejection of the null hypothesis at the 1%, 5%, and 10% of significance level are highlighted with one (*), two (**) and three (***) asterisks, respectively.

Panel (A). BEKK model

	NBP	ZEE	TTF
c_{11}	-0.56*	-1.87*	-0.35*
c_{22}	0.02	7.6×10^{-8}	-0.35*
c_{12}	-0.12*	-0.90*	2.7×10^{-10}
a_{11}	0.20*	0.44*	-0.66*
a_{12}	0.12*	0.05	0.61*
a_{21}	0.63*	-0.34***	0.06*
a_{22}	0.23*	0.47*	0.95*
b_{11}	0.93*	0.71*	0.10*
b_{12}	0.03*	-0.09*	0.66*
b_{21}	-0.29*	-1.19*	0.35*
b_{22}	0.82*	-0.19**	-1.61*
g_{11}	-0.05	-0.34*	-0.61
g_{12}	-0.03	-0.04	0.03*
g_{21}	-0.92*	0.34	-0.30***
g_{22}	0.31*	0.05	0.38*

Panel (B). Summary statistics for the standardized residuals

	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$
Skewness	1.07*	0.45*	8.15*	0.46*	1.62*	0.46
Kurtosis	6.31*	1.99*	119.68*	2.81*	10.77*	1.67
Q(20)	20.48	15.58	6.43	5.19	15.31	14.36
Q^2(20)	15.05	33.83**	19.80	21.73	6.08	47.31*

Table 7. Seasonal covariance model estimates

This table reports the estimates of equation (16). Other comments are identical to those of Table 5.

Panel (A). Volatility seasonal model

	NBP	ZEE	TTF
c_{11}	3.12*	3.12*	2.56*
c_{22}	1.05*	1.30*	1.10*
c_{12}	1.37*	1.54*	1.37*
a_{11}	-1.95*	-2.32*	-1.15*
b_{11}	8.05*	6.90*	5.84*
a_{22}	0.01*	-0.34*	-0.47*
b_{22}	0.44*	0.73*	0.67*
a_{12}	-0.19*	-0.40*	-0.64*
b_{12}	1.00*	1.11*	1.41*

Panel (B). Summary statistics for the standardized residuals

	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$
Skewness	0.52*	1.02*	1.42*	0.78*	0.29*	0.38*
Kurtosis	10.77*	11.15*	19.19*	7.88*	15.20*	3.01*
Q(20)	18.98	8.84	25.21	14.69	16.43	13.63
$Q^2(20)$	291.05*	223.01*	74.70*	157.80*	35.53**	60.73*

Table 8. Seasonal-basis covariance model estimates

This table shows the estimates of equation (17). Other comments are identical to those of Table 5.

Panel (A). Volatility seasonal model

	NBP	ZEE	TTF
c_{11}	3.47*	3.50*	2.87*
c_{22}	1.10*	1.41*	1.18*
c_{12}	1.46*	1.67*	1.49*
a_{11}	-2.21*	-2.27*	-1.93*
a_{22}	-0.11*	-0.25*	-0.21*
a_{12}	-0.27*	-0.37*	-0.45*
a	1.04*	1.10*	0.86*
b	1.29*	1.44*	0.87*
c	-3.49*	-2.88*	-2.98*

Panel (B). Summary statistics for the standardized residuals

	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$
Skewness	0.53*	1.01*	1.43*	0.79*	0.21**	0.32*
Kurtosis	10.81*	10.97*	19.30*	7.94*	15.37*	3.83*
Q(20)	18.92	8.57	25.93	14.74	16.37	12.24
$Q^2(20)$	289.82*	52.35*	183.09*	155.45*	32.78**	66.86*

Table 9. Hedging effectiveness in weekly hedges

This table displays the risk reduction achieved by each hedging strategy: naive, OLS without the basis (see equation (4)), OLS with the basis (see equation (8)), BEKK (see equation (15)), seasonal (see equation (16)) and seasonal-basis (see equation (17)). The *in sample* results are computed for the first 5 years and then a moving window of five years is used to compute the *out-of-sample* results. In the second row of each panel, the unhedged spot position variance is reported and constitutes the base to calculate the risk reduction achieved with each hedging strategy. This variance is computed as $VAR[\Delta^k S(t)]$ and $VAR[\Delta^k S(t) - \hat{\lambda}(F(t,T_k) - S(t))]$ in the 'standard' and Ederington and Salas (2008) approaches, respectively. Variance of each hedging strategy is computed as $VAR[\Delta^k S(t) - \hat{b}_t \Delta^k F(t,T_i)]$ and $VAR[\Delta^k S(t) - \hat{b}_t \Delta^k F(t,T_i) - \hat{\lambda}(F(t,T_k) - S(t))]$ in the standard and 'E&S(2008)' approaches, respectively. Spot and futures variations are defined as in Table 1 and b_t represents the hedging ratio. *Ex ante* hedging ratios are forecasted values in *t*–1 and each time the moving window sample moves ahead the model is estimated again. Those strategies with largest risk reduction in each panel are indicated with an asterisk (*).

	In the sample		**Out of the sample**	
	Standard approach	E&S(2008) approach	Standard approach	E&S(2008) approach
Panel (A). Hedging one-week spot risk in NBP				
Period	Dec. 3rd, 1997 – Feb.19th, 2003		Feb. 26th, 2003 – Mar. 26th, 2014	
Spot variance (no hedged)	13.14	9.95	45.76	42.81
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naive (*b*=1)	16.76	24.91	31.83	42.55
OLS w/o basis	19.40	30.01	31.85	45.91
OLS with basis	19.26	30.19*	30.48	46.12
Seasonal	19.06	29.98	30.31	45.79
Seasonal-basis	19.03	30.15	31.83	46.81*
BEKK	16.87	29.04	8.69	17.04
Panel (B). Hedging one-week spot risk in ZEE				
Period	Oct. 20th, 1999 – Jan.5th, 2005		Jan. 12th, 2005 – Mar. 26th, 2014	
Spot variance (no hedged)	11.39	8.76	52.38	57.25
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naive (*b*=1)	19.87	28.80	29.65	39.52
OLS w/o basis	19.96	29.53	29.94	43.61
OLS with basis	18.68	30.79	28.38	42.71
Seasonal	17.98	30.64	29.30	43.52
Seasonal-basis	17.81	30.64	30.91	44.44*
BEKK	22.02	33.17*	28.94	41.52
Panel (C). Hedging one-week spot risk in TTF				
Period	Jan. 7th, 2004 – Mar. 25th, 2009		Apr. 1st, 2009 – Mar. 26th, 2014	
Spot variance (no hedged)	7.90	6.75	1.34	1.32
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naive (*b*=1)	33.62	41.65	34.18	46.46*
OLS w/o basis	34.36	44.65	33.14	46.18
OLS with basis	31.58	46.95	26.28	44.71
Seasonal	29.38	47.37*	27.73	42.96
Seasonal-basis	28.51	46.83	30.94	45.04
BEKK	30.99	47.28	26.36	40.55

Table 10. Hedging effectiveness in long-time hedges

This table is similar to Table 6, but using monthly data frequency and only linear regression and naïve hedges because of data sample restrictions. The *in-sample* results are computed from the beginning of each time-series until March 2006. In the *out-of-sample* period, OLS hedging ratios b_t (see equations (4) and (8)) are forecasted values and each time a new observation is added the model is estimated again.

	In the sample		**Out of the sample**	
	Standard approach	E&S(2008) approach	Standard approach	E&S(2008) approach
Panel (A). Hedging one month spot risk in NBP.				
Period	December 1997 – March 2006		April 2006 – March 2014	
Spot variance (not hedged)	185.98	94.93	54.30	74.53
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (*b*=1)	43.69	81.09*	19.88	78.58
OLS w/o basis	55.82	78.98	-24.01	78.98*
OLS with basis	54.75	69.38	-34.41	76.23
Panel (B). Hedging one month spot risk in ZEE.				
Period	October 1999 – March 2006		April 2006 – March 2014	
Spot variance (not hedged)	129.58	76.48	53.50	57.12
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (*b*=1)	59.23	75.83	46.01	85.87
OLS w/o basis	63.82	75.28	37.24	87.22*
OLS with basis	62.50	77.45*	38.61	86.97
Panel (C). Hedging one month spot risk in TTF.				
Period	January 2004 – March 2006		April 2006 – March 2014	
Spot variance (not hedged)	26.84	12.68	8.89	10.86
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (*b*=1)	48.16	75.47	46.73	87.63*
OLS w/o basis	50.81	85.16	42.59	85.58
OLS with basis	47.11	89.19*	17.00	87.55
Panel (D). Hedging three-month spot risk in NBP				
Period	December 1997 – March 2006		April 2006 – March 2014	
Spot variance (not hedged)	226.35	101.36	151.71	190.65
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naive (*b*=1)	34.72	70.70	-21.45	92.10*
OLS w/o basis	36.87	73.31	-13.16	83.56
OLS with basis	36.75	73.56*	-51.83	91.23
Panel (E). Hedging six-month spot risk in NBP				
Period	December 1997 – March 2006		April 2006 – March 2014	
Spot variance (not hedged)	235.89	91.67	370.18	420.71
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naive (*b*=1)	16.55	66.80	-6.54	93.08*
OLS w/o basis	16.66	69.71	11.79	74.11
OLS with basis	15.25	73.39*	-32.86	92.25

Table 11. Variances of spot returns and basis

This table reports the annualized variances of spot returns ($\Delta^k S(t)$) and basis ($F(t,T_k)$- $S(t)$) for hedges of 1, 3, and 6 months using the monthly frequency data set. The *in-sample* results are computed from the beginning of each time-series until March 2006. In the *out-of-sample* period, results are computed from April 2006 until March 2014.

	In the sample		**Out of the sample**	
	Spot return	basis	Spot return	basis
1 month (NBP)	2072.28	764.88	823.80	691.20
1 month (ZEE)	1561.80	518.88	642.00	441.00
1 month (TTF)	269.88	148.56	106.68	71.40
3 months (NBP)	866.88	587.52	642.28	667.20
6 months (NBP)	474.76	538.34	736.90	516.52

Table 12. Hedging effectiveness: VaR and ES

This table reports the Value at Risk (VaR) and Expected Shortfall (ES) calculated at the 5% significance level. VaR and ES are estimated using the historical simulation approach based on the empirical distributions or actual returns.

Hedging strategy(*)	*VaR*(1%)		*VaR*(99%)		*ES*(1%)		*ES*(99%)	
	Spot	Hedged	Spot	Hedged	Spot	Hedged	Spot	Hedged
Week hedges								
NBP	-18.80	-12.27 (34.74)	17.21	14.79 (14.06)	-26.68	-23.56 (11.70)	36.97	23.97 (35.16)
ZEE	-22.73	-20.41 (10.21)	18.74	13.95 (25.53)	-29.67	-25.96 (12.50)	42.68	29.58 (30.69)
TTF	-5.24	-3.45 (34.22)	4.30	3.74 (12.99)	-7.07	-4.32 (38.90)	5.42	5.16 (4.92)
Month hedges								
NBP	-27.06	-13.79 (49.02)	12.05	11.21 (6.98%)	-30.95	-9.71 (68.62)	26.86	19.02 (29.18)
ZEE	-23.84	-7.76 (67.43)	10.15	5.69 (43.95)	29.97	-10.86 (63.75)	22.76	14.89 (34.60)
TTF	-11.10	-4.66 (58.02)	4.74	1.73 (63.54)	-11.29	-5.94 (47.37)	8.24	5.09 (38.25)
Three months hedges								
NBP	-47.50	-12.71 (73.24)	17.40	5.26 (69.78)	-50.39	-16.84 (66.56)	30.80	19.95 (35.24)
Six months hedges								
NBP	-63.75	-14.24 (77.67)	21.66	11.08 (48.85)	-71.61	-19.88 (72.24)	31.97	19.92 (37.69)

(*)Best performing strategies in each panel in the last column in Tables 9 and 10. Percentage reduction of the original spot position statistics under E&S (2008) approach are displayed between brackets below hedged portfolio statistics.

Annex II: figures

Figure 1. European spot and futures natural gas markets.
Spot price (——) and the first to ‘delivery’ futures price (- - -)

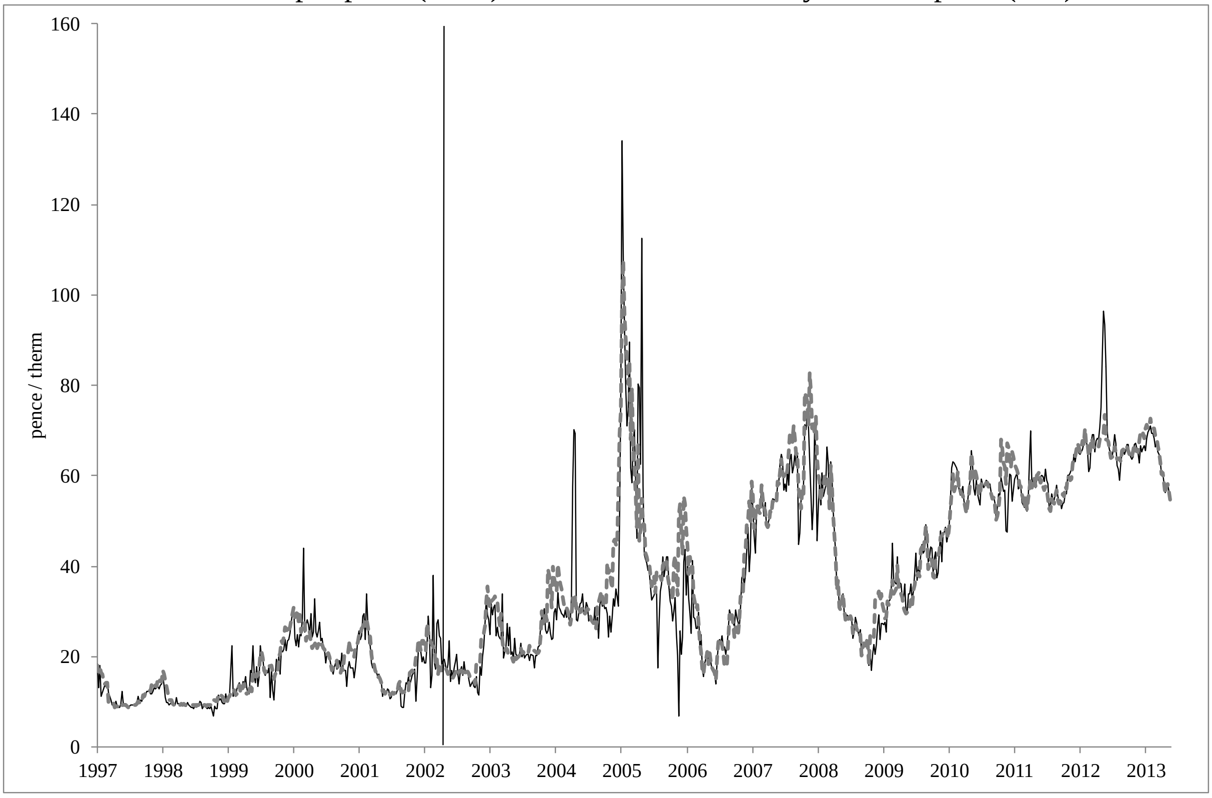


Figure 1(a). NBP spot and first to ‘delivery’ futures contract.

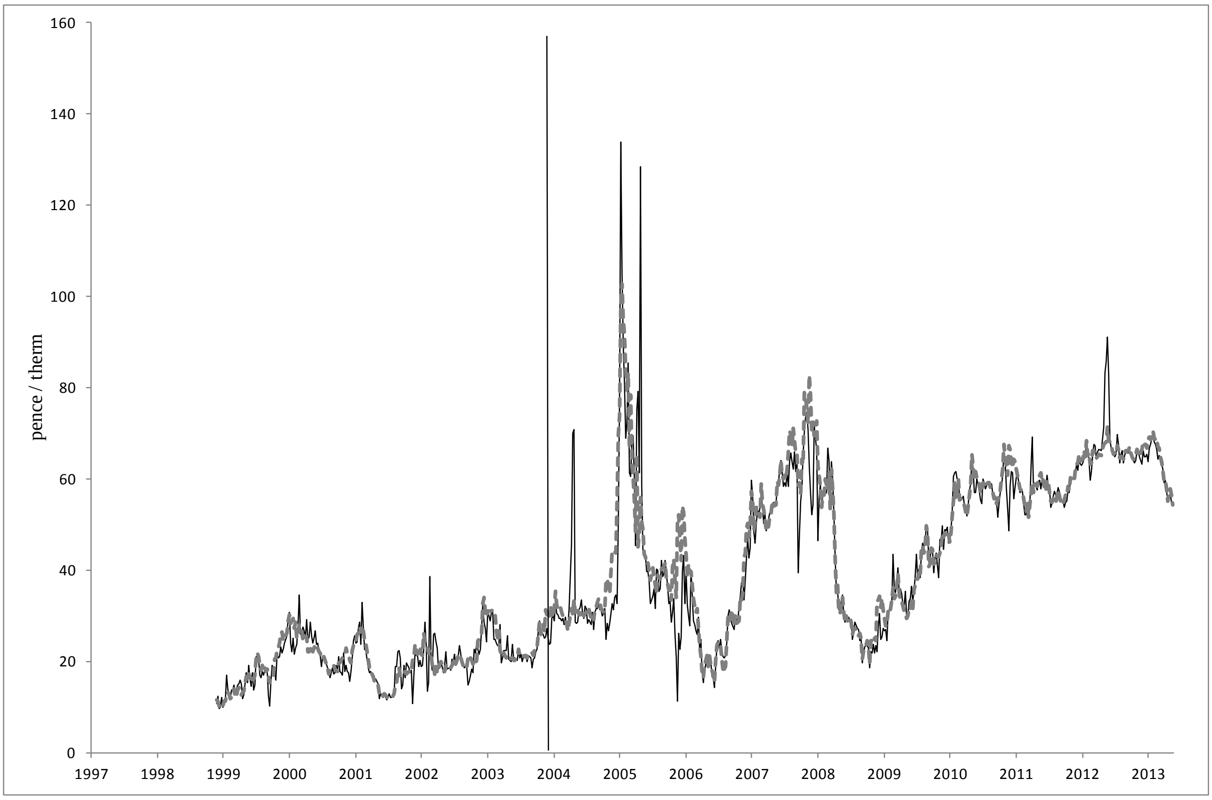


Figure 1(b). Zeebrugge spot and first to 'delivery' futures contract.

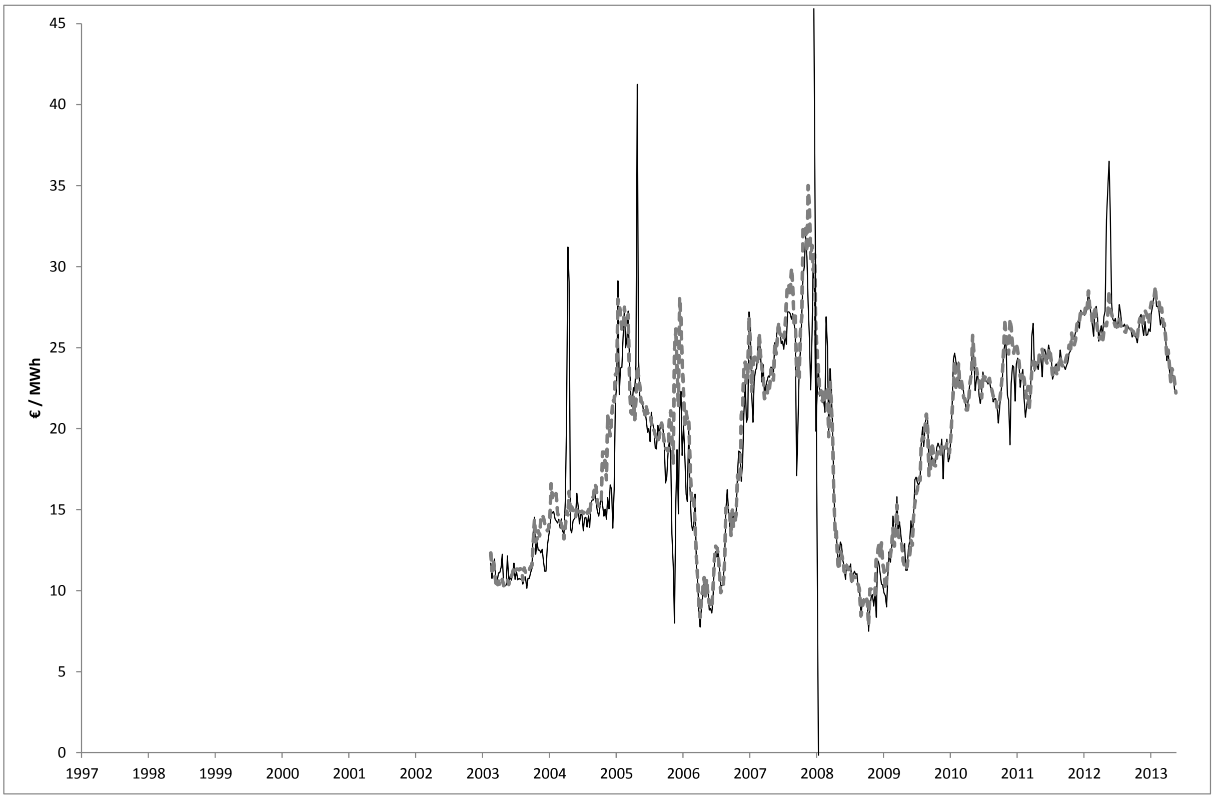


Figure 1(c). TTF spot and first to ‘delivery’ futures contract.

Figure 2. Seasonal basis.

13-week centered moving average basis at NBP (——), Zeebrugge (- - -), and TTF (···) are computed as the futures front contract price minus daily spot price.

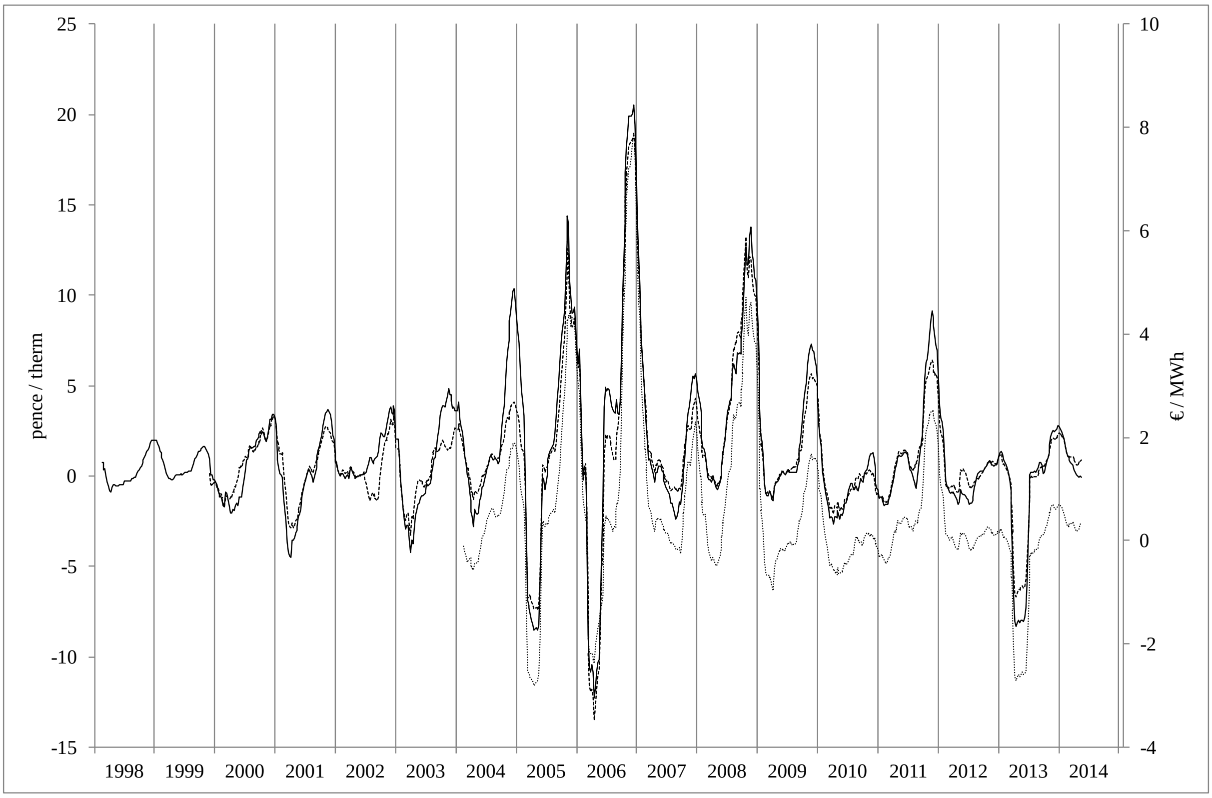


Figure 3. Seasonal volatility

NBP spot volatility (——) and its front monthly futures volatility (- - -). Standard deviation of a 13-week centered moving window returns are reported.

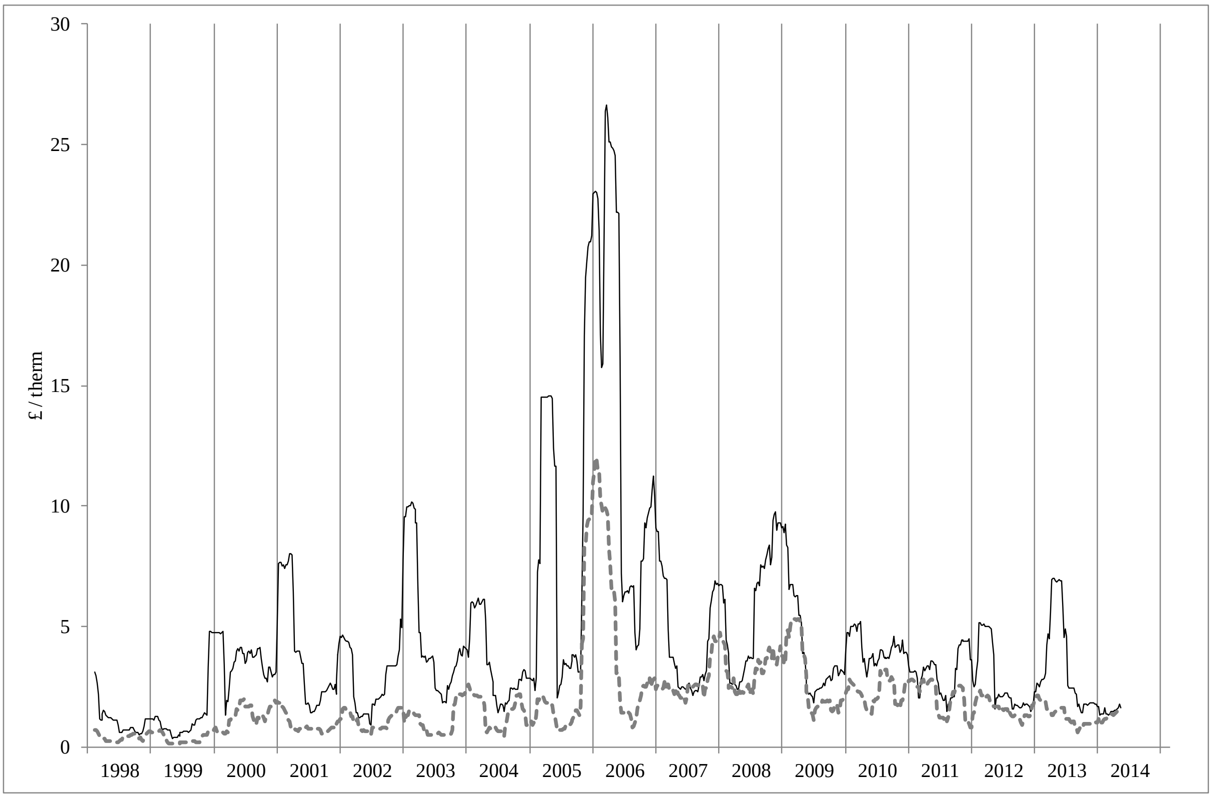


Figure 4. Annualized conditional volatilities

Notes. In each graph, the solid line (——) and the dashed line (- - -) corresponds to the annualized conditional volatility for the seasonal-basis and BEKK models, respectively. The displayed conditional volatilities are estimated in the 'one-week' hedging period models for NBP prices. The vertical line separates the *ex post* and *ex ante* (five year moving window) hedging periods.

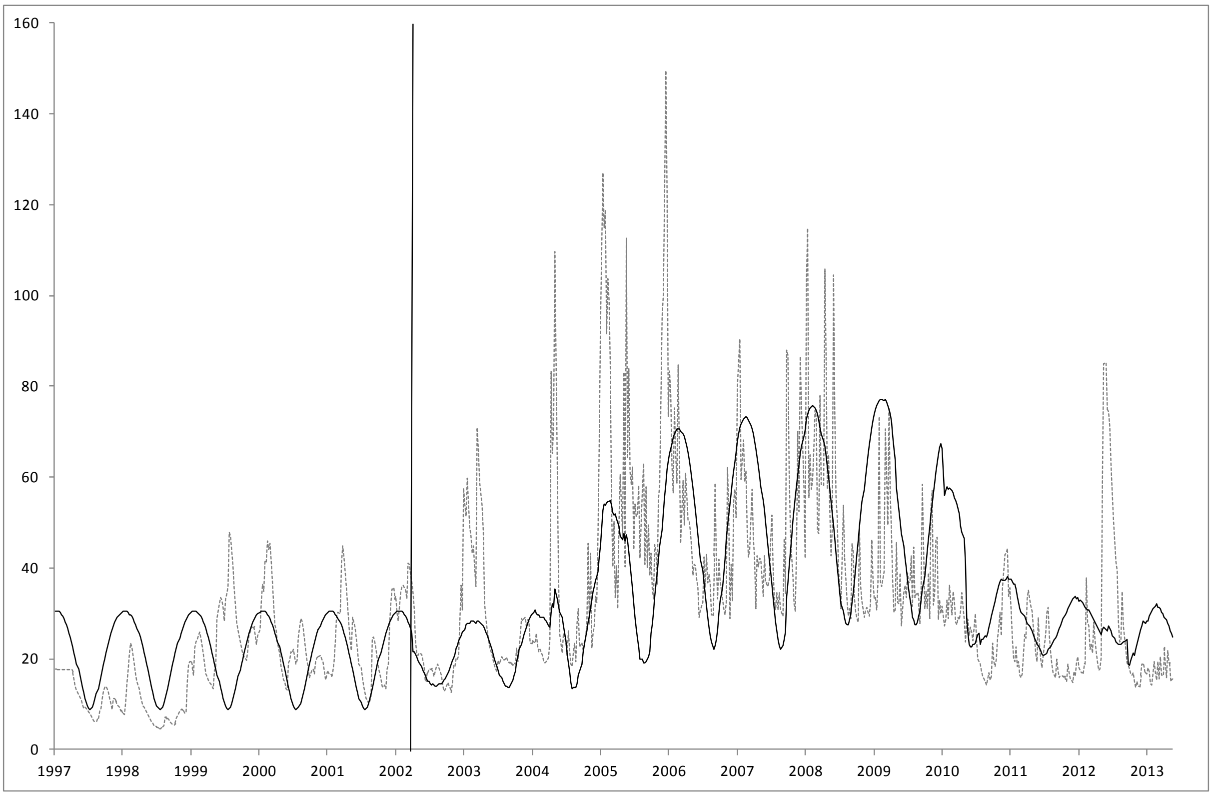


Figure 4(a). Spot annualized volatility

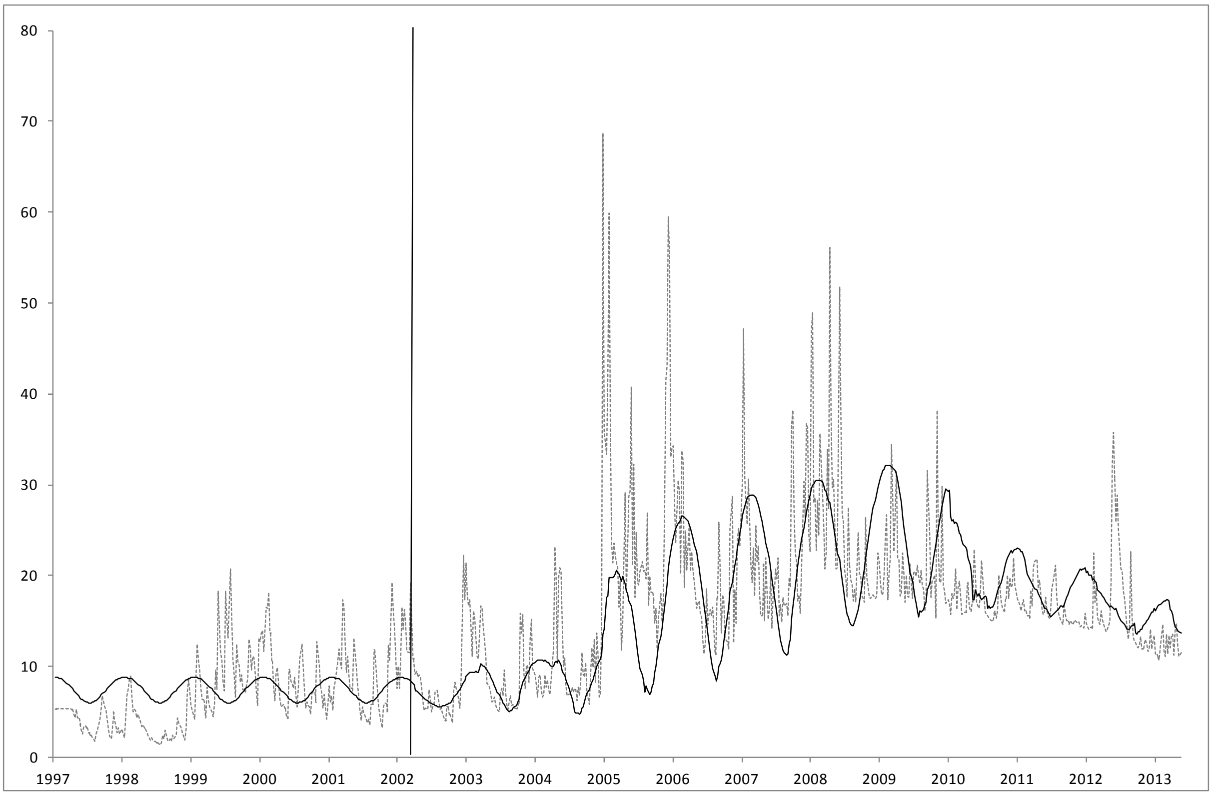


Figure 4(b). First to ‘delivery’ annualized volatility

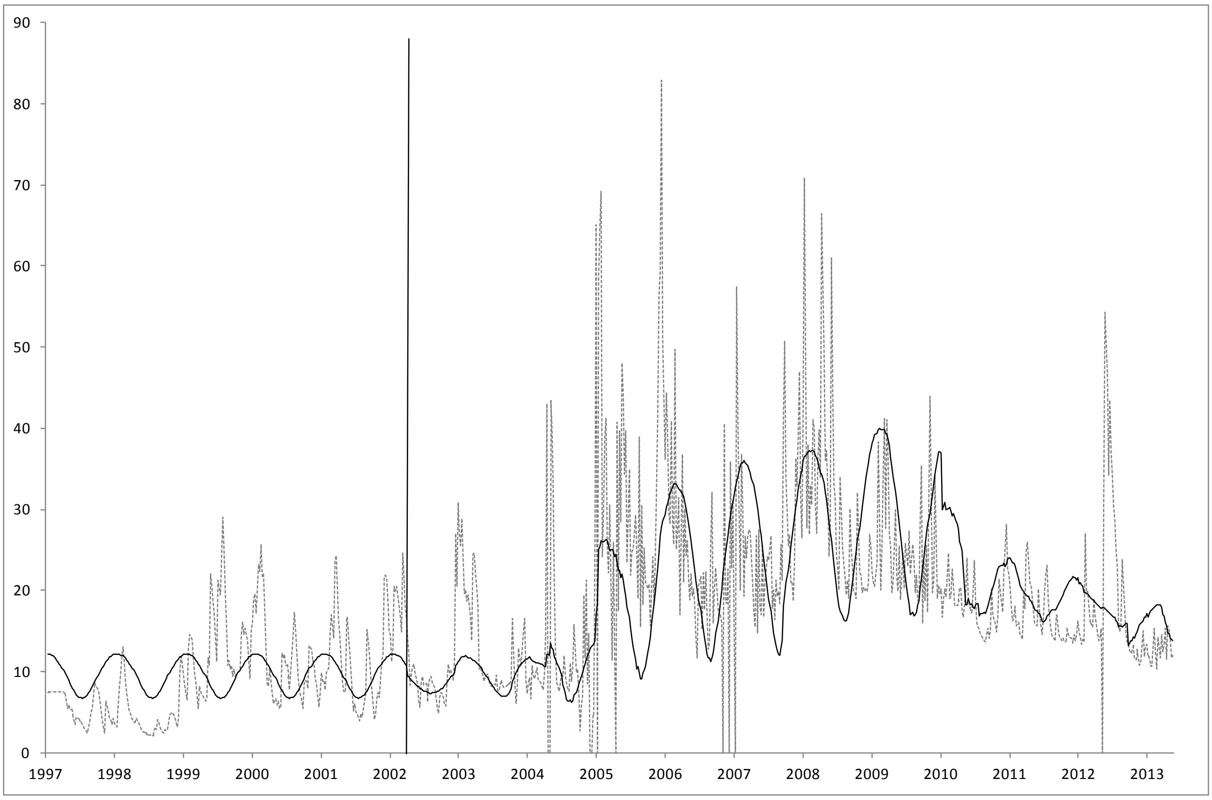


Figure 4(c). Annualized covariance between spot and futures

Figure 5. Hedging ratios.

Notes. The vertical line separates the *ex post* and *ex ante* hedging periods. The vertical line separates the *ex post* and *ex ante* (five years moving window) hedging periods.

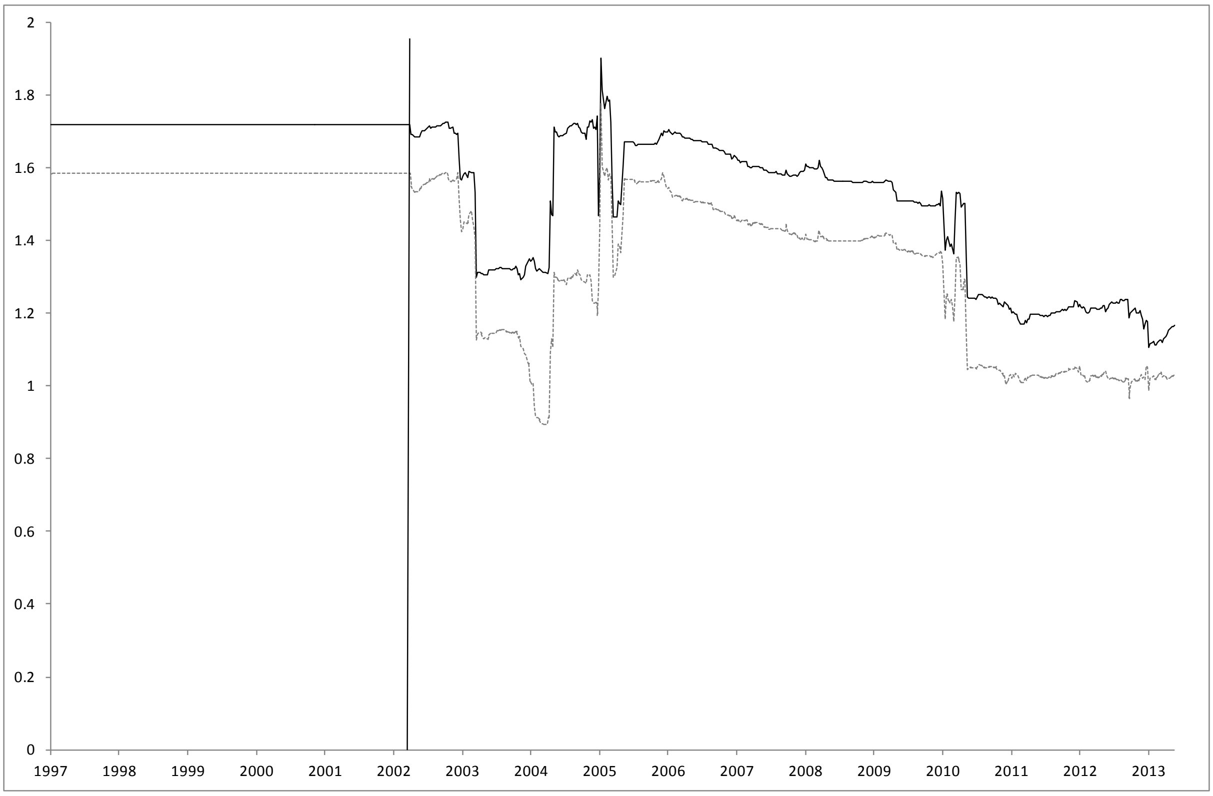


Figure 5(a). OLS hedging ratios estimated with equation (8) are represented with continuous lines (——) and OLS hedging ratios estimated with equation (4) are represented with dashed lines (- - -).

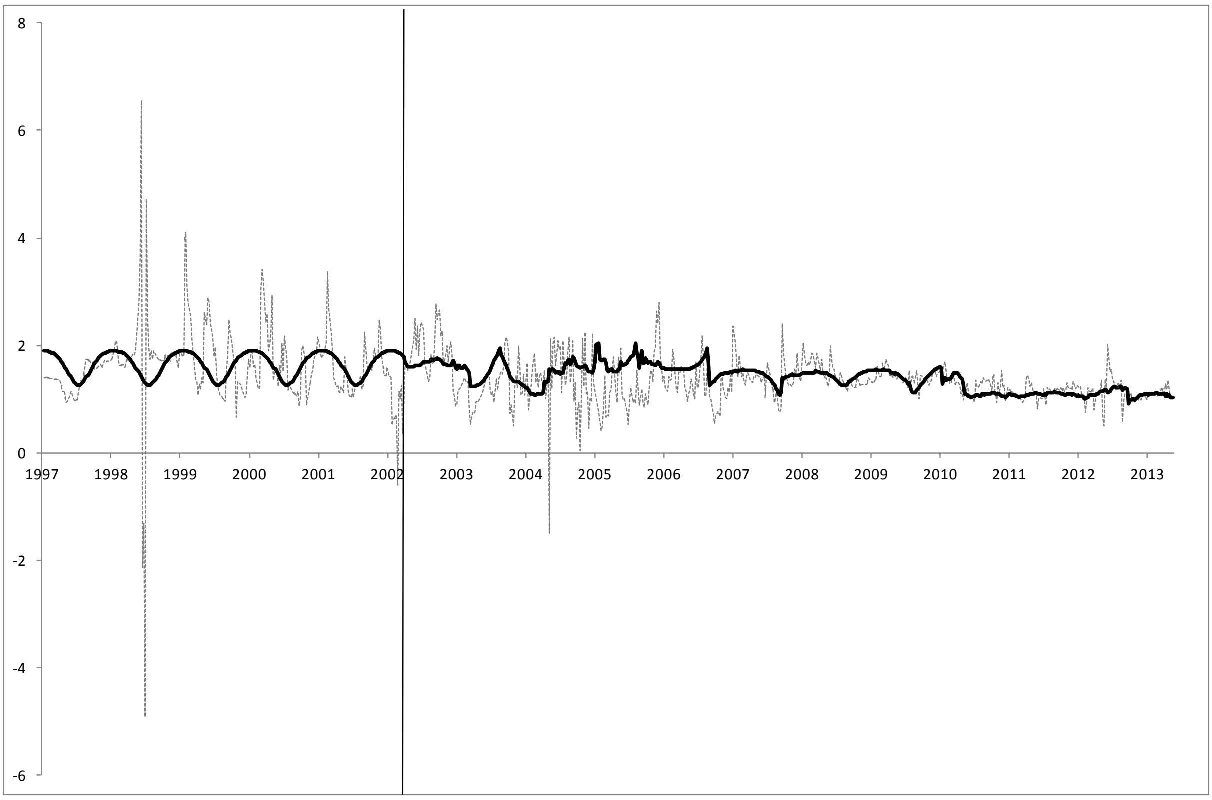


Figure 5(b). BEKK hedging ratios are represented with continuous lines (——) and seasonal hedging ratios are represented with dashed lines (- - -).

Chapter II

ANALYSIS OF RISK PREMIUM IN UK NATURAL GAS FUTURES

1. Introduction

Risk premium can be seen as the expected return of holding until delivery a position in a futures contract. For long-term strategies, positions can be taken in long-term maturity futures; or alternatively, short-term maturity futures can be rolled over until the strategy horizon is attained. Before making a decision, a portfolio manager takes into account the transaction costs incurred in each alternative and the usual trade-offs existing between the use of long-term maturity futures that exactly fit the desired planning horizon and the higher liquidity of short-term maturity futures. Therefore, obtaining an exact measure of risk premium for both alternatives is an insightful piece of information for agent decision making.

Based on equilibrium considerations, forward risk premiums should be fundamentally related to economic risks and the willingness of different market participants to bear these risks (Longstaff and Wang 2002, page 1888). Szymanowska et al. (2014) argue that conventional long-term and accrued short-term risk premiums differ as each is related to different risk factors. Accrued short-term risk premiums will be closely related with the spot price risk, while long-term premiums mainly reflect the risk present in the convenience yield.[1] One important and innovative aim of this paper is to compare, for a specific case, if long-term and accrued short-term risk premiums are driven by different risk factors based on equilibrium considerations.

We have addressed our attention towards the UK natural gas futures market because of the scarcity of previous studies on the risk premiums in UK natural gas futures. As far as we know, the only published paper studying risk premiums in the UK natural gas futures market is Haff et al. (2008). This study is more focused on explaining convenience yield, spread between futures contracts and basis. Their only observation on risk premiums is that risk premiums vary between 5% and 8% (1 to 5 months ahead) using 75 monthly observations for each maturity. Haff et al. (2008) measured risk premiums by comparing the futures price near to maturity with futures prices taken 1 to 5 months

[1] Using energy futures traded at NYMEX (heating oil, gasoline, and crude oil) for the period March 1986 to December 2010, Szymanowska et al. (2014) obtain annualized risk premiums slightly above the accrued risk premiums in the rollover strategy when taking values of about 10% for all the analysed maturities. Differences between both premiums were not significant.

before that maturity. The underlying spot price when the risk premiums are computed is not taken into account. As we use the true underlying spot price, we use futures with one to six months to delivery. In this way, for example, the three months to maturity risk premium in Haff et al. (2008) can be obtained by subtracting one to four months from delivery risk premiums. We have checked this computation in our data set and it is about the same. Modjatehedi and Movassagh (2005a) studied the natural gas futures pricing in the US using the futures prices a few days prior to futures maturity as a proxy for the spot price. Within this data set, they found a negative time-varying futures bias according to the normal backwardation.[2] Explanations for why this market is in barkwardation are provided in Modjatehedi and Movassagh (2005b) although any of these explanations are supported with further evidence that some state rules prohibited gas buyers entering the futures markets or a brief comment on the lack incentives (because they can transfer prices to their retail customers). Then the normal backwardation is seen as a reward for long positions taken by speculators in the futures market as a consequence of the short-hedging pressure from the supply side. In the US natural gas market, Wei and Zhu (2006) found that one-month ahead forward contracts in the Henry Hub contained a positive and significant risk premium with values ranging between 3% and 11%. Nevertheless, none of the above-mentioned references present a model or evidence relating these premiums with equilibrium arguments. Furthermore, they seem to conclude without any evidence that the forward bias may be caused by the concentration in the supply side for the UK of a few large producers and the opposite reasoning for the US market, where production is spread among many small companies. In Heather (2015, section 5.6) several surveys on European hubs are examined. One way of assessing the competitiveness of the wholesale gas market is by looking at the level of market concentration. Heather's (2015) opinion is

[2] In the classical view of hedging pressure as a determinant of futures premiums, when the forward bias is negative (futures prices below expected spot prices), the futures market is said to be in *normal backwardation* (short hedging pressure). On the other hand, if the *forward bias* is positive (futures prices above expected spot prices), the futures market is said to be in *contango* (long hedging pressure); see Duffie (1989, chapter 4) and Hull (2006, p. 121) for more details about these concepts. Bessembinder (1992) find a strong relationship between futures returns and hedging pressure, or a return to speculation in agricultural contracts. These results support the classical view of Keynes (1930) of hedging pressure as a determinant of futures premiums and indicate a degree of segmentation between asset markets and some futures markets.

contrary to the existence of market concentration in the UK. He shows that market concentration in the NBP market is the lowest in Europe. The top three sellers represent about the 50% of the hub supply and the number of active players in the NBP has increased from about 20 in the mid-2000s to maybe 40 in 2014. Heather (2015) argues that active players are both simultaneously present in the physical OTC and futures markets. The general opinion of the author is that Britain has a fully liberalised, established, and successful traded gas market, which has reached maturity.

The UK natural gas futures market deserves attention as it is the European benchmark for natural gas and the front contract seems to lead the remaining European natural gas futures and spot markets.[3] Futures negotiated at the Intercontinental Exchange (ICE) are increasing in importance and liquidity – and represent more than one-third of gas negotiated at NBP (Heather, 2010). The UK natural gas market is the most liquid in Europe. The vast majority of gas contracts are over-the-counter but the regulated futures market is growing in importance (Heather, 2010). The futures British gas market is operated by InterContinental Exchange (ICE) Europe. Forward and futures contracts are underwritten to be delivered on the *national balancing point* (NBP), the notional point in the UK transmission system (NTS).[4] The ICE natural gas futures contract for NBP was launched in January 1997 and has become the benchmark for natural gas trading in Britain and continental Europe. Continental gas markets were developed following the path the British had marked. The UK and continental Europe are linked through The Interconnector – a gas pipeline which connects the UK gas entry point at Bacton to the Belgian port of Zeebrugge. It has been open since 1998 and

[3] Price discovery has been studied in Schultz and Swieringa (2013), using intraday data of futures and spot prices of the most important markets in Europe. NBP spot in the short run and ICE prompt in the short and long run are leading the equilibrium. It is also found that spot markets are weakly linked and this suggests significant market frictions may exist between the various natural gas hubs in Europe. Results in Kao and Wan (2009) show that NBP futures prices lead spot prices – both in mean and volatility.

[4] Liberalization of the natural gas market began in the UK with the 1995 Gas Act. The following year, the Network Code created the NBP hub enabling third party access to the British gas network. A national transition system then changed the balancing regime from monthly to daily. Thereafter, all gas in the UK must be traded through the NBP hub which is traded "entry paid", i.e. already in the NTS. The network code also included the NBP`97 contract, a common standardized trading contract required for trading gas in the British market and in which all natural gas agreements must be based. This contract, along with changes in the balancing, enabled the development of the British hub. Important changes in the contractual conditions and trading system were introduced in the British natural gas market in 2004-2005 after the Enron and TFX collapse, resulting in a new regulation, the Uniform Network Code in 2005.

enables the flow of gas between British and continental markets. Since its launch, UK prices have converged progressively to continental prices (Heather (2012)).

Therefore, our study is innovative in several ways: (i) it is the most in-depth study to date on risk premiums of NBP futures; (ii) there are no precedents (other than for the US futures markets) in which a pair-wise comparison between the accrued risk premiums and long-term conventional risk premiums is made; and (iii) because it is the first time the question of whether risk premiums in natural gas futures are priced according equilibrium considerations has been investigated; and (iv) our study has tried to establish if both risk premiums respond to the same or different risk factors under equilibrium considerations. We study the seasonal pattern in both cases and we estimate a regression model reflecting risk premium response to risk factors. If risk factors can explain time-varying realized risk premiums it can be understood that an important part of expected risk premiums are priced according to risk considerations – and not priced by a simple bias obtained as a result of several agents dominating the market.

Mu (2007), Suenaga et al. (2008) and Alterman (2012) report several features of natural gas price volatility. The most relevant result for our study is that volatility is seasonal and closely related with weather shocks and storage levels. This is because demand seasonality is closely related with weather seasonality. Winter jumps in demand are more difficult to buffer because the active storage management is less flexible due to the high marginal cost production and demand inelasticity. Our intuition extracted from previous literature on natural gas prices is that conventional and accrued risk premiums probably contain a strong seasonal pattern.[5] Our results confirm this intuition although we obtain significant differences between both magnitudes, both in size and risk factor sensitivity. Our empirical results confirm that differences are reduced when liquidity in the long-term futures contract increases.

[5] Nevertheless, we must mention that the price seasonality of natural gas in the US is decreasing sharply. Non-conventional shale gas is abundant and represents a downward pressure on winter prices. Furthermore, the increased number of cooling systems and the growing use of natural gas are raising summer prices (see Henaff et al. (2013)). We believe this phenomenon is not yet as important in European countries.

Several empirical contributions are produced in this paper. Firstly, all risk premium average values are significantly different to zero, positive, and increasing with time to delivery. Most importantly, the accrued risk premium in rollover strategies is significatively larger than conventional risk premiums and increases with time to delivery. Specifically, for strategy horizons between 3 and 6 months, this difference increases from 1% to 10%**,** or equivalently from 4% to 20% per annum.[6] We have also shown that these differences can be partially explained by liquidity arguments in the futures market. Secondly, it is the first time that risk premium in day-ahead forwards has been measured in this market. The average value of the day-ahead risk premium is 0.5% per day and this is statistically significant. Thirdly, all risk premiums are significantly larger and more volatile in winter. The significant and highest monthly values correspond to January and February. Finally, risk premium time-variation is analyzed using a regression model on risk factors affecting potential participants in equilibrium models. It is shown that unexpected reservoir shocks, demand shocks under tight supply conditions, and spot price volatility are significant explicative variables – and the signs reflect equilibrium models implications on storable commodities.

The rest of this paper is organized as follows. Section 2 summarizes the risk premium approach to futures pricing, and describes the general features of the empirical research. Section 3 describes the data set used in the empirical application. Section 4 describes the results obtained. Section 5 measures the influence of transaction costs in our results. Section 6 concludes with a summary of the main results and some final remarks.

2. The risk premium approach to futures hedging

Fama and French (1987) distinguish and relate the two common views on how futures prices are formed. Based on arbitrage arguments, the theory of storage sustains that futures prices are obtained by adding to the spot price the cost of carrying the underlying asset until futures maturity. This cost

---

[6] Risk premiums in futures pricing literature are mostly expressed as returns (log-returns, percentage returns, or realized returns). We follow the Nobel Prize winner in economics Eugene F. Fama in his work Fama and French (1987) and use mostly non-annualized realized returns or log-returns. Other authors using these metrics are Lucia and Torró (2011), Haff et al. (2008) and Wei and Zhu (2006).

includes the interest forgone, the marginal storage cost, and the convenience yield from the asset availability. Under the second view, the futures price is dicomposed into the expected spot price at futures maturity and the expected premium, also known as forward premium or forward bias. In this second approach forward premium represents the equilibrium compensation for bearing the price and/or demand risk for the underlying commodity (Longstaff and Wang 2002, page 1888).

Fama and French (1987) observe that both views of futures pricing are compatible. That is, variation in the risk premium, or in the expected spot price, translates into variation in cost of carry constituents. For energy commodities like natural gas, futures price may be below current spot price when storage levels are low and the convenience yield exceeds financial and storage costs. This situation used to happen in winter when demand for natural gas as a heating fuel is high. The second theory explanation would be that futures prices are below the current spot price because spot prices are expected to decrease for the warm season when the storage level increases and demand for natural gas decreases.

Duffie (1989, page 98) points out that there are few assets that adhere exactly to the theory of storage since storage costs, interest rates, and convenience yield until delivery are sometimes uncertain and transaction costs may be important. Specifically, in the case of UK natural gas financial derivatives, Cartea and Williams (2008) offer some reasons that explain the difficulty of cash-and-carry pricing. During winter cold snaps, the rates at which gas can be injected or withdrawn from storage systems are limited and cannot stop a rise in spot prices. Cartea and Williams (2008) observe that limitations in the withdrawal capacity of the system limit the possibility of taking advantage of rising prices. Consequently, the direct application of the cost of carry theory to exploit arbitrage opportunities is not as clear as the theory might suggest.

In equilibrium models, risk premiums are linked to risk factors affecting potential market players. The presence of risk premiums in futures prices is evidence of the fact that agents act in the market according to risk considerations. The specificities of each market (such as the importance of the natural gas as energy fuel for a country and its electricity market, the degree of concentration in the supply or demand, technology, dependence on imports, environmental regulation, and the price of alternative energy) can also help to explain deviations between forward and expected spot prices. Nevertheless, it is possible that stationary time-varying risk premiums exist and it might be very difficult to split the futures price into expected spot price and risk premiums. In this last case, evidence relating risk premiums with risk variables and supported with theoretical equilibrium models is a good way to support the equilibrium content to the forward bias. The equilibrium content examination of the forward premium will be based in three variables: inventories shocks; demand shocks; and spot price volatility.

Inventory decisions are important for commodities because they link current and expected commodities (Routledge et al. (2000)). Kawai (1983) proposes an equilibrium model for the price of a storable commodity for which there is a futures market. When the model reaches the equilibrium, risk premiums are negatively related with inventories levels. In a very related context, Cartea and Williams (2008) introduce a time-varying market price of risk when valuing derivative assets in the UK natural gas market. In their model, the market price of risk is a linear function of unexpected shocks in storage levels. They obtain a negative relationship between both variables. That is, when storage levels are higher (lower) than expected, the market price of risk decreases (increases). It is important to remark that the forward risk premiums and market price of risk are two concepts closely related but different.[7] The empirical evidence of this idea has been observed in Lucia and Torró (2011) and Furió and Meneu (2010) in electricity markets where indicators of abnormal levels in hydro reservoirs significantly describe risk premium behavior. Following Furió and Meneu (2010), we propose to use inventory changes as a proxy of unexpected inventories shocks. Results will show that there is a negative relationship between risk premium and storage variation. That is, risk premiums are higher (lower) when inventories decrease (increase).

[7] In the absence of arbitrage opportunities, the derivative risk premium, expressed as the expected return, μ_i, minus the risk-free rate, r, can be related with the market price of risk, λ, times the amount of risk, σ_i, derivative i holds: $\mu_i - r = \lambda \times \sigma_i$. The market price of risk is equal across all derivatives contingent on the same source of risk, but the risk premium is specific to each of these derivatives (see Bollen (1997)). For futures prices, the risk premium is reduced to μ_i as no investment is needed in futures markets to take a position (see Kolos and Ronn (2008)).

Seasonality in energy prices during the year are mainly caused by weather and its effects on energy demand, especially when supply is tight (see e.g. Bessembinder and Lemmon (2002), Longstaff and Wang (2002) and Cartea and Villaplana (2008)). Tight conditions in supply can be identified with decreasing or low storage levels. We put all this conditions together in a variable. That is, we obtain an indicator of demand shocks in tight conditions. A similar indicator was used in Furió and Meneu (2010) to explain risk premium dynamics in Spanish electricity markets using unexpected shocks in demand whenever the level of expected hydroelectricity energy capacity is below its historical mean value.

Finally, spot price volatility is used to explain forward risk premiums because of its equilibrium implications. Beck (1993) proposes an equilibrium model in which risk premium and spot price volatility are positively related. He argues that agents use spot price volatility to predict spot price risk because in storable commodities spot price variances are serially correlated. Therefore, spot price variance should be incorporated in equilibrium forward risk premium.

Following Fama and French (1987) and Lucia and Torro (2011), we review some basic well-known definitions and relate this classical view with the innovative approach to futures pricing in Szymanowska et al. (2014). Under the risk premium approach to futures pricing, the futures price is split into the expected spot price on the delivery date and a premium, which is known as the risk premium, the futures forward/premium, or the futures/forward bias. To fix notation, let $S(t)$ denote the spot price for natural gas to be delivered at time *t*, let $F(t-j,t)$ denote the futures price observed *j* days/months before *t* when the natural gas is due to be delivered, and let $P(t-j,t)$ denote the risk premium. The basic futures pricing relationship under the risk premium approach can be written as follows:

$$F(t-j,t) = E_{t-j}\left[S(t)\right] + P(t-j,t) \tag{1}$$

where $E_{t-j}[\cdot]$ denotes the conditional expectation operator at time $t-j$. The above-defined premium is also called the *ex ante* or expected premium, to be distinguished from the *ex post* or realized premium, which is defined as the difference between the futures price and the spot price at maturity:

$$RP(t-j,t) = F(t-j,t) - S(t) \tag{2}$$

Since liquidity decreases as futures maturities become more distant, futures markets liquidity risk will be a crucial factor explaining the difference between the risk premium involved in a very liquid trading strategy such as is the rollover strategy, and the conventional risk premium appearing in a equivalent position in a long-term maturity futures contract with much less liquidity. In Szymanowska et al. (2014) conventional risk premium for a specific futures contract maturity is split in two parts: a liquidity premium plus a rollover premium. The rollover premium is computed by adding the risk premiums of a rollover strategy in the front contract until the specific maturity is attained. The liquidity premium can be obtained by subtracting the conventional from the rollover premium.[8]

Following Szymanowska et al. (2014), the expected rollover premium can adapted as

$$ROP(t-j,t) = E_{t-j}[F(t-1,t) - S(t)] + \sum_{k=1}^{j-1} E_{t-j}\left[F(t-(k+1), t-(k-1)) - F(t-k, t-(k-1))\right] \tag{3}$$

for j = 3, 4, …, n months before delivery. Hence, realized rollover premiums will be computed by taking realized prices instead of expected prices. In the above equation, we have added the first term $E_{t-j}[F(t-1,t) - S(t)]$. The second term is the summation of the one month premiums accrued in the rollover strategy in the front contract. As in Szymanowska et al. (2014) risk premiums are

[8] In Szymanowska et al. (2014), the rollover and the liquidity premiums are called spot and term premiums, respectively.

calculated on futures maturity and not on the delivery date, when the true underlying price is known. Note that in our notation, "*t*–1" is the last trading day of the futures contract considered and '*t*' corresponds to the delivery day or month. The first rollover will appear with j = 3, that is, three months before the delivery date '*t*'. Therefore, for one and two months before delivery, only conventional risk premiums can be computed. In this way, the one month before delivery date will correspond to the front futures contract maturity date, and the two months before the delivery date will match the last date in which a futures position is opened in a rollover strategy, consequently no further risk-premium accumulation is possible. The day-ahead risk premium will be computed as the difference between the average of day-ahead forwards and the average of the system average price within each month.

But further to this, it is important to analyze time-variation in both cases. To provide compelling evidence of time-varying expected premiums, we will estimate a regression model reflecting risk premium response to risk factors without imposing a specific structure implied by an equilibrium model. If risk factors can explain time-varying realized risk premiums it can be understood that an important part of expected risk premiums are priced according to risk considerations and not a simple bias without economic significance. The regression model we propose is the following

$$F(t-j,t)-S(t)=a+bSD(t-j)+cUWD(t-j)+dDUK(t-j)+\varepsilon(t-j,t) \qquad (4)$$

for j = 1 *day*, 1, 2, 3, 4, 5 and 6 months to delivery. *SD* refers to the standard deviation of the daily *system average price* in the month $t-j$. $DUK(t-j)$ refers to the natural gas reservoir level change in the United Kingdom in the month $t-j$, that is $UK(t-j)-UK(t-j-1)$. *UWD* represents unexpected demand shock when conditions of tight supply are given. Specifically, this variable is computed as the unexpected heating degree days (UHDD, henceforth) in winter when inventory levels decrease. The intermediate variable UHDD represent the difference between the historical value since 1974[9] and the observed daily accrued heating degree days for each month within the year for the United Kingdom.[10] Winter is defined by taking the following months: October, November, December, January, February and March.[11] Finally, for the day-ahead forwards, the dependent variable is computed in each month as the average value of $F(t-1\,day,t)-S(t)$ within each month (as we are using monthly data frequency). Equation (4) will also be estimated for rollover realized premiums to obtain the special features of this pricing approach.

The introduction of storage levels to explain risk premium dynamics is crucial. The influence of storage levels in natural gas futures prices and volatility has been studied by Efimova and Serletis (2014), Suenaga et al. (2008), Mu (2007), Henaff (2013) and Wei and Zhu (2006). Storage level seasonality influences natural gas spot and futures pricing is critical. Under the theory of storage, inventory seasonalities generate seasonalities in the marginal convenience yield – and in the basis (see Fama and French, 1987, p. 56). The effect of demand and supply shocks on spot and futures prices will depend on storage levels and how they are managed. Any demand or supply shock is easily offset when reservoirs are high – but when reservoirs are low, a demand, or supply shock is more difficult to balance (and will be somewhat persistent, allowing spot and futures prices to increase). Haff et al. (2008) found in the UK natural gas market that inventory levels from the UK and the European Union are significant on short-run two and three month futures spreads (prompt and basis) as predicted by the theory of storage. In our empirical study, the inventory levels for the EU did not add any significant value.

Finally, for the difference between realized accrued rollover premiums and conventional realized risk premiums we propose to extend the above regression model introducing a new variable, open

---

[9] 1974 is the base year in the heating degree days database.

[10] Natural gas demand has a clear seasonal pattern related to weather variables (temperature, wind speed, humidity, and precipitation). Prices respond to this pattern and especially to any surprises relative to historical values. Li and Sailor (1995) and Sailor and Muñoz (1997) find in a sample of US states that temperature is the most significant weather factor explaining electricity and gas demand.

[11] That is, $UWD(t-j)=UHDD(t-j)\times DUK(t-j)\times I(DUK(t-j)<0)\times I(t-j\in WINTER)$. Where $I(\cdot)$ is an indicator function, taking the value 1.0 if the condition inside brackets is true and 0.0 otherwise. Seasons in the Intercontinental Exchange comprise a strip of April-September or October-March.

interest (*OI*), representing the liquidity of the futures markets. Specifically, we propose the following model

$$ROP(t-j,t)-\left[F(t-j,t)-S(t)\right]=a+bSD(t-j)+cUWD(t-j) \\ +dDUK(t-j)+eOI(t-j)+\varepsilon(t-j,t) \quad (4)$$

where *OI* refer to the monthly average of the daily open interest of each futures contract. This is an interesting sensitivity analysis for traders, as they will ponder how liquidity levels in a long-term futures maturity strategy acts on the difference between risk premiums. Under the hypothesis that the difference between risk premiums is positive, a negative and significant coefficient in this variable would be interpreted as the disposition to pay more for a higher liquidity strategy. When liquidity in the long-term futures maturity is high, the willingness to pay a higher premium in a rollover strategy in the front contracts will decrease.[12]

3. Data

In this section, we compile the data sources in Table 1 and offer several graphical representations. The time period of the study starts on April 2000 and finish on February 2015. Futures prices, traded volumes, and open interests are obtained directly from the ICE. There is a wide range of natural gas derivative contracts (forward, futures, and options) traded at the ICE. The most important of the regulated contracts are monthly futures, especially the front month contract (which is the most liquid of all traded contracts). The numbers appearing in Figure 1(a) evidence this fact and it is especially true when looking at the trading volume, where first and second contracts closest to maturity represent more than the 80 per cent of total trades. To avoid low liquidity problems the study has been limited to the six-month contracts nearest to delivery.[13] In all these cases, the

[12] Using the difference between the open interest in the front contract and the open interest in the long-term futures maturity, we obtain the same results and conclusions.
[13] Results and conclusions obtained for those monthly contracts with seven to twelve months to delivery are consistent and similar to those results and conclusions reported here for contracts with between one and six months to delivery.

average daily traded volume and open interest is above 100 and 6000 contracts, respectively. Average monthly time series of daily traded volume and open interest are shown in Figures 1(b) and 1(c), respectively. It can be appreciated that volumes and open positions steadily increase in the second half of the sample. Furthermore, from a casual visual inspection in this second half of the sample, it can be inferred that open interest values describe a seasonal pattern, taking peak and off-peak values in summer and winter respectively.

Monthly time series are built by taking closing prices on the day prior to maturity of the front contract – avoiding in this way the 'last trading day' turbulences in the front contract. In the ICE, final futures settlement covers the difference between the last closing price of the futures contract and the *system average price* (SAP henceforth) in the 'delivery period' of all the calendar days of the month. Monthly SAP thus becomes the underlying spot reference on which expectations are projected and futures contracts priced. To catch seasonality in futures prices and the risk premiums contained in them, we use weather and storage level variables (see Figures 2 and 3). The following section will add more comments on these variables. Figures 4 to 7 display all the risk premium time series described in the previous section. Finally, Figure 8 reports the monthly volatility time series of the SAP measured as the standard deviation of daily returns within each month.

High prices and risk premiums (see Figures 2 to 7) correspond to events mostly related with geopolitics: the dispute between Russia and the Ukraine about the price of gas and transit combined with abnormally cold weather (3 March 2005, 22 November 2005, January 2009, February 2012) and the Libyan civil war (spring 2011). However, the most dramatic shortcoming and peak was during February and March 2006 when a cold spell was combined with a fire at the Rough natural gas storage facilities in the North Sea – preventing access to nearly 80% of total UK storage just as withdrawals from storage were about to begin (see Giulietti et al., 2011).

4. Results

Tables 2, 3 and 4 report the descriptive analysis of realized conventional risk premiums, rollover premiums, and the difference between them. All these tables contain two panels: one for realized returns defined in monetary units (pence) and another for log-returns. We use realized returns and log returns because both measures can be attractive for market agents. Alexander et al. (2013) argue that "...for assets with prices that can jump, log returns can be highly inaccurate proxies for percentage returns even when measured at the daily frequency". Consequently, we decided to report both returns measures in these tables. These compact tables report relevant information for the risk premium analysis: (1) average values for the whole period; (2) average values for each month of the year; (3) average values for the winter and summer seasons; and (4) volatility for winter and summer seasons.

Average values for the whole period are significantly different to zero, positive, and increase with the time to delivery. When futures prices are above the expected spot prices, the futures market is said to be in contango because the long hedging pressure generates higher futures prices as a compensation for short positions taken in the futures market (see Duffie (1989) for more details about this concept). Day-ahead risk premium value is 0.41 pence or 0.5 per cent. This is the first time this risk premium has been obtained and means that simultaneously selling day-ahead natural gas and buying it the following day on the spot market will report a 0.5% return of the total asset value every day, or equivalently, about 180 per cent return per year if it is repeated every day. Conventional risk premiums vary between 0.99 and 6.14 pence or between 4.32 and 15.64 per cent for those contracts with between one and six months remaining to delivery. Finally, the rollover premiums are significatively higher at between 0.24 and 3.52 pence; or between 1.26 and 10.54 per cent for maturities of between three and six months (see Tables 3 and 4). The intuition behind this result is that 'n' times a rollover strategy on the front contract contains higher risk premiums than futures strategies based on contracts with 'n' months left to reach maturity. As we will see later, this result seems to be related with agent preferences for the most liquid contracts and their willingness to pay more to take longer positions in the most traded contracts.

Winter months contain the highest risk premiums in both cases (Tables 2 and 3). The most significant and highest months are January and February. These are the two months with highest demand for heating. In these months, the risk of unexpected demand and inventory shocks is highest. Therefore, short positions in futures markets will claim an extra premium. Finishing a futures trading strategy in January with positions engaged six months before would imply an average risk premium at delivery of 23.96 and 33.56 per cent for a single trade and rollover strategy, respectively. Differences are not significant in these cases but are significant in summer months, when rollover risk premiums are significatively higher, but with lower values than in winter. To sum up, operating rollover strategies have a higher cost and this difference is significant in summer months (see the median equality test in Table 4, Panel A). Finally, the winter volatility of both risk premiums is significantly higher than summer volatility when returns are considered (see Panel A in Tables 2 and 3).

To obtain further evidence for seasonal behavior in the UK natural gas market, system average price volatility and skewness are reported in Table 5. In each month or season, volatility, and skewness are computed considering the daily system average price contained during that period. Volatility results in Table 5 are easy to interpret: volatility in winter months is greater. This result is statistically significant in raw returns reported in Panel A. For raw returns, we do not find any significant skewness coefficient, but for log-returns some of the skewness coefficients are significant and with predominantly negative values. However, skewness coefficient differences between winter and summer months are not statistically significant. This result is contrary to the prediction of the equilibrium model proposed by Bessembinder and Lemmon (2002) for pricing electricity futures. Electricity returns are positively skewed because of the existence of upward spikes when expected demand is high relative to capacity, or when demand is more variable. In this situation, futures prices are increased to compensate for the skewness, since short futures positions can incur large losses. In natural gas, we do not find any significant positive skewness and the importance of the spikes is much less relevant than in the case of electricity. As natural gas is a storable commodity, unexpected demand shocks are more easily offset than with electrical power.

Equations 4 and 5 are estimated for conventional risk premiums, rollover premiums, and the difference between them – the results are reported in Tables 6, 7, and 8, respectively. Results for conventional and rollover risk premiums are similar. In both cases, it can be observed that the standard deviation is always significant at 1 per cent of significance level. Consequently, risk premiums are closely related with uncertainty measured by the standard deviation of the SAP in the month in which the futures price is taken. That is, futures risk premiums are very sensitive to the spot market risk. This result was expected for rollover risk premiums, where this coefficient takes larger values than for conventional risk premiums (see Szymanowska et al. (2014)). In the same way, both risk premiums have a positive and significant sensitivity to unexpected demand shocks under tight supply conditions. Finally, the sensitivity to our proxy to unexpected inventory shocks is negative in all cases and statistically significant in most. To obtain some insight on the convenience yield response to the analysed risk factors we repeated the estimation shown in Tables 6 and 7 – but substituting the risk premium with the convenience yield in equation (4). Results for the convenience yields (Appendix: Tables A1, A2, A3 and A4) are very similar to those obtained for the risk premiums. Analogous significativeness and sign of estimated coefficients for each risk factor and determination coefficients were obtained. As the Theory of Storage states, a negative relationship between convenience yields and inventories exists, and convenience yield and demand shocks are positively related. Therefore, as Fama and French (1987) predicted, variation in the expected premium translates into variation in the marginal convenience yield, or vice versa.

To obtain some feature showing the difference between rollover and conventional risk premiums, we have introduced open interest in equation (5) as an explicative variable. Results in Table 8 show that this coefficient has a negative value and is statistically significant in three out of four cases. That is, larger liquidity in the futures contract used to compute the conventional risk premium reduces the differences between both risk premiums. Therefore, as the rollover strategy is the most liquid and contains the highest risk compensation, this result reinforces the idea that agents prefer to trade with the most liquid contracts and are willing to pay more for them. The coefficient sign of all the remaining variables are positive and significant in most cases. An increase in the spot price volatility, or an unexpected positive demand shock in tight supply conditions, increases the difference between both premiums. Moreover, the response of the difference between both premiums to our proxy of unexpected inventory shocks is positive and increases with time to delivery. The reason for this coefficient being positive seems to be the greater negative response of conventional premiums – rather than rollover risk premiums – to unexpected inventory shocks (see Tables 6 and 7). This greater negative response, and the computation of the difference in risk premiums as the rollover minus the conventional risk premium, produces a positive coefficient in Table 8.

5. Transaction costs in rollover and long-time strategies

Agents will take strategic decisions in futures markets depending on the transaction costs involved, and this is especially important when comparing rollover strategies in the front contract versus strategies based on longer futures maturity contracts. The most important transaction cost in futures markets is the bid-ask spread. To compute the importance of the bid-ask spread involved in each futures strategy, we have taken bid and ask prices at hourly frequencies from October 23, 2014, until October 23, 2015 (2560 hourly observations). The bid-ask spreads obtained for the 1, 2, 3, 4, and 5 months to maturity are 0.08, 0.10, 0.16, 0.23 and 0.41 pence; respectively. The relative bid-ask spreads obtained over the average between bid and ask prices are 0.17%, 0.23%, 0.36%, 0.50% and 0.89% respectively. We can observe that bid-ask spread cost is almost neutral in our analysis as rollover 'n' times involves approximately the same costs as taking positions with futures contracts with 'n' months remaining to maturity (or 'n+1' months to delivery). Rolling over five times in front implies paying five times 0.17% (that is 0.85%); while the bid-ask spread in a five-month to maturity contract (six months to delivery) is 0.89%. Finally, extracted from ICE rules in May 2014, the total member trading fees for a contract would be £1.90 for NBP monthly contracts (about 0.003% of the underlying value). Therefore, the transactions costs because of market fees will vary between 0.003% and 0.015% for one to five transactions for the furthest considered case (six months to delivery).

A detailed presentation of all the transaction costs involved in each strategy is shown in Table 9. It can be observed that the relative value of all the transaction costs maintain a proportionality over time to maturity. That is, rolling over on the front contract ‘n’ times will have similar transaction costs as taking positions in a futures contracts with ‘n’ months to maturity. If we compare the average values of the difference between rollover and conventional risk premiums appearing in Table 4 (1.26, 3.75, 7.03 and 10.54 per cent) with the last column in Table 9 (0.113, 0.156, 0.189 and -0.048 per cent), we can conclude that transaction costs do not have an important role in the risk premium analysis carried out throughout the paper.

6. Conclusions

The seminal paper of Szymanowska et al. (2014) decomposes conventional risk premiums into two parts: the "spot component" and “term component". In our study, the spot component is named rollover risk premium and the term component is obtained as the difference between the rollover and conventional risk premiums. From this viewpoint, our results agree with the results of Szymanowska et al. (2014) as risk premiums in the UK natural gas futures are dominated by the ‘spot component’ (rollover risk premiums exceed conventional risk premiums). Our study enriches this new approach to futures pricing in several ways. Seasonal patterns for mean and volatility are detected in rollover risk premiums, conventional risk premiums, and in the difference between them. Winter months feature higher and more volatile risk premiums. One important and innovative aim of this paper is to examine, for a specific case, if long-term and accrued short-term risk premiums are driven or not by different risk factors based on equilibrium considerations. Risk factors specific to this market and supported with theoretical equilibrium models are considered: volatility of the spot price returns; unexpected demand shocks under tight supply conditions; and unexpected inventory shocks. Results show that these risk factors can explain time-varying realized risk premiums in a similar way to that predicted by the theory in both cases. We can conclude that an important part of expected risk premiums is priced according to risk considerations. Finally, liquidity in the futures markets seems to be the most explicative variable explaining the difference between both risk premiums. This result implies that liquidity arguments are important for futures pricing and preference for liquidity is paid when a rollover strategy is taken.

The results in this paper are important for the design of most trading strategies in this futures market. Comparing rollover risk premiums with conventional risk premiums is an important preliminary issue before deciding which futures maturity to use – or if the higher liquidity of the front contract compensates for a higher rollover risk premium.

References

Alexander C., Prokopczuk M., and Sumawong A. (2013) The (de)merits of minimum-variance hedging: Application to crack spread. Energy Economics 36, 698-707.

Alterman, S. (2012) Natural gas price volatility in the UK and North America. Oxford Institute for Energy Studies.

Beck, S. E. (1993). A rational expectations model on time varying risk premia in commodities futures markets: Theory and evidence. International Economic Review 34, 149-68.

Bessembinder, H. (1992) Systematic Risk, Hedging Pressure, and Risk Premiums in Futures Markets. The Review of Financial Studies 5, 637-67

Bessembinder, H. and Lemmon, M.L. (2002). Equilibrium Pricing and Optimal Hedging in Electricity Forward Markets. The Journal of Finance, 57, 1347-1382.

Bollen, N. P. B. (1997). Derivatives and the price of risk. The Journal of Futures Markets 17, 839-854.

Cartea, A., and Villaplana, P. (2008) Spot price modelling and the valuation of electricity forward contracts: The role of demand and capacity. Journal of Banking and Finance 32, 2502-19.

Cartea, Á., and Williams, T. (2008) UK gas markets: The market price of risk and applications to multiple interruptible supply contracts. Energy Economics 30, 829-846.

Duffie, D. (1989) Futures Markets. Prentice Hall, Englewood Cliffs, New Jersey.

Efimova, O., and Serletis, A. (2014) Energy Markets Volatility Modelling using GARCH. Energy Economics 43, 264-273.

Fama, E. F., and French, K. R. (1987). Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage. Journal of Business, 60, 55-74.

Furio, D., and Meneu, V. (2010) Expectations and forward risk premium in the Spanish deregulated power market. Energy Policy 38, 784-93.

Giulietti, M., Grossi, L., and Waterson, M. (2011) A Rough Examination of the value of gas storage. Warwick Economic Research Papers No 967. Department of Economics, University of Warwick.

Haff, I. H., Lindqvist, O., and Loland A. (2008) Risk premium in the UK natural gas forward market. Energy Economics 30, 2420-2440.

Heather, P. (2010) The evolution and functioning of the traded gas market in Britain. Oxford Institute for Energy Studies, NG 44.

Heather, P. (2012). Continental European Gas Hubs: Are they fit for purpose? Oxford Institute for Energy Studies, NG 63.

Heather, P. (2015). The evolution of European traded gas hubs. The Oxford Institute for Energy Studies. OIES Paper: NG 104.

Henaff, P., Laachir, I., and Russo, F. (2013) Gas storage valuation and hedging. A quantification of the model risk. Working paper. ArXiv:1312.3789v1[q-fin.PR] 13 Dec 2013.

Hull, J. C. (2006) Options Futures and Other Derivatives. 6th. Edition, Englewood Cliffs, New Jersey.

Kao, C.W., and Wan, J.Y. (2009) Information transmission and market interactions across the Atlantic – an empirical study on the natural gas market. Energy Economics 31, 152-161.

Kawai, M. (1983). Price volatility of storable commodities under rational expectations in spot and futures markets. International Economic Review 24, 435-459.

Keynes, J. M. (1930) A treatise on money, Volume II. The applied Theory of Money, London. Macmillan and Company.

Kolos, S. P., and Ronn, E. I. (2008) Estimating the commodity market price of risk for energy prices. Energy Economics 30, 621-41.

Li, X. and Sailor, D.J. (1995) Electricity use sensitivity to climate and climate change. World Resource Review 7, 334-346.

Longstaff, F. A., and Wang, A. W. (2002) Electricity forward prices: A high-frequency empirical analysis. The Journal of Finance 59, 1877-1900.

Lucia, J.J., and Torro, H. (2011) On the risk Premium in Nordic electricity futures prices. International Review of Economics and Finance 20, 750-63.

Modjtahedi B., and Movassagh, H. (2005a) Bias and backwardation in natural gas futures prices. The Journal of Futures Markets 25, 281-308.

Modjtahedi B., and Movassagh, H. (2005b) Natural-gas futures: Bias, predictive performance and the theory of storage. Energy Economics 27, 617-37.

Mu, X. (2007) Weather, storage and natural gas price dynamics: Fundamentals and volatility. Energy Economics 29, 46-63.

Routledge, B. R., Seppi D. J., and Spatt, C. S. (2000) Equilibrium forward curves for commodities. The Journal of Finance 55, 1297-1338.

Sailor, D.J. and Muñoz, J.R. (1997) Sensitivity of electricity and natural gas consumption to climate in the USA - methodology and results for eight states. Energy, 987-998.

Schultz, E., and Swieringa, J. (2013) Price discovery in European natural gas markets. Energy Policy 61, 628-634.

Suenaga, H., Smith, A., and Williams J. (2008) Volatility dynamics of NYMEX natural gas futures prices. The Journal of Futures Markets 28, 438-463.

Szymanowska, M., De Roon, F., Nijman, T., and Van den Goorbergh, R. (2014) An Anatomy of Commodity Futures Risk Premia. The Journal of Finance 69, 453-482.

Wei, S.Z.C. and Zhu, Z. (2006) Commodity convenience yield and risk premium: The case of US natural gas market. Energy Economics 28, 523-534.

Annex I: Tables

Table 1. Data sources

Variable	Description	Unit	Time period	Source
Futures prices	National Balancing Point (NBP) futures price for one to six months	pence/therm	Apr. 2000-Feb. 2015	Intercontinental Exchange (ICE)
Day-ahead forward prices	Delivery next working day after assessment/trade.	pence/therm	Apr. 2000-Feb. 2015	Platts
System average price (SAP)	Average price of all gas traded via the on-the-day commodity market (OCM) mechanism for the gas day in UK	pence/therm	Apr. 2000-Feb. 2015	APX-ENDEX
Volume	Volume traded for the indicated trade day	pence/therm	Apr. 2000-Feb. 2015	Intercontinental Exchange (ICE)
Open interest	Open interest at the close of business on a trading day	pence/therm	Apr. 2000-Feb. 2015	Intercontinental Exchange (ICE)
Heating degree days (HDD)	HDD index: deviation of the daily accrued HDD for each month from the historical value of the HDD in the UK	Degrees Celsius	Jan. 1974-Feb. 2015	European Commission: Agri4Cast Data Portal
Storage	Working gas stocks of natural gas reservoirs for EU-28 and UK	Million cubic meters (mcm)	Apr. 2000-Feb. 2015	IEA and Howard Rogers from OIES

Table 2. Risk premiums

Taking monthly frequency data from April 2000 until February 2015 (179 observations) *ex post* risk premiums in ‘*t*’ are computed as $F(t\text{–}j,t) - S(t)$ in Panel A and $100\times\log(F(t\text{–}j,t)/S(t))$ in Panel B for j = 1 day, 1 month, …, 6 months. For the day-ahead forwards, the average value of the daily difference: $F(t-1\,day,t)-S(t)$ in Panel A and $100\times\log(F(t\text{–}1,t)/S(t))$ in Panel B is computed. Mean values and their *p*-value for the *t*-statistic mean zero hypotheses tests are reported between brackets. Winter season is defined by taking the following months: October, November, December, January, February and March. For summer season, the remaining months are taken. In ‘Mean equality’, ‘Median equality’ and ‘Variance equality’ rows, the *t*-statistic, the *Kruskal-Wallis* and the *Levene* tests statistics and their *p* values in brackets are reported.

	Panel A. Returns.						
	Time to maturity						
	1 day	1 months	2 month	3 months	4 months	5 months	6 months
Whole period	0.41 [0.00]	0.99 [0.02]	2.73[0.00]	4.24[0.00]	5.09[0.00]	5.62[0.00]	6.14[0.00]
January	0.68[0.11]	3.46[0.03]	7.93[0.03]	10.35[0.00]	12.09[0.01]	12.42[0.02]	12.34[0.01]
February	0.51[0.28]	1.54[0.37]	4.81[0.05]	8.95[0.02]	10.87[0.00]	12.33[0.02]	12.86[0.03]
March	0.49[0.19]	-2.21[0.20]	-0.01[1.00]	2.57[0.44]	5.07[0.17]	6.32[0.17]	8.13[0.19]
April	0.20[0.16]	1.15[0.25]	0.81[0.53]	2.45[0.35]	4.20[0.17]	4.45[0.17]	6.09[0.10]
May	0.17[0.25]	-0.14[0.88]	1.32[0.34]	1.11[0.52]	1.84[0.47]	3.19[0.27]	3.12[0.30]
June	0.19[0.19]	1.17[0.17]	1.35[0.30]	2.59[0.18]	2.04[0.37]	2.19[0.44]	3.25[0.29]
July	0.24[0.22]	0.24[0.82]	1.65[0.24]	0.88[0.61]	1.64[0.45]	0.84[0.73]	0.98[0.74]
August	-0.00[0.98]	1.09[0.14]	2.62[0.09]	3.40[0.03]	2.34[0.16]	2.90[0.17]	1.96[0.38]
September	0.28[0.21]	-1.41[0.32]	-0.14[0.93]	0.94[0.60]	1.70[0.36]	0.86[0.71]	1.46[0.61]
October	0.98[0.00]	3.02[0.10]	3.86[0.17]	4.66[0.11]	5.48[0.10]	6.30[0.07]	5.16[0.13]
November	0.94[0.09]	0.78[0.72]	3.83[0.25]	5.21[0.22]	5.34[0.12]	6.79[0.11]	7.52[0.10]
December	0.22[0.43]	3.04[0.13]	4.32[0.15]	7.18[0.13]	7.79[0.14]	7.98[0.08]	9.68[0.07]
Winter	0.64[0.00]	1.65[0.03]	4.17[0.00]	6.53[0.00]	7.80[0.00]	8.72[0.00]	9.29[0.00]
Summer	0.18[0.01]	0.34[0.40]	1.28[0.02]	1.89[0.01]	2.29[0.01]	2.38[0.02]	2.81[0.02]
Mean equality	2.74[0.01]	1.56[0.12]	2.23[0.02]	2.89[0.00]	3.11[0.00]	3.16[0.00]	2.89[0.00]
Median Equality	4.57[0.03]	3.34[0.07]	2.38[0.12]	4.03[0.04]	5.32[0.02]	6.09[0.01]	4.48[0.03]
Winter Volatility	1.46	6.90	11.07	13.35	14.44	16.04	17.79
Summer Volatility	0.63	3.83	5.14	6.85	8.07	9.39	10.58
Variance Equality	16.81[0.00]	7.47[0.01]	23.77[0.00]	17.30[0.00]	13.19[0.00]	9.95[0.00]	8.28[0.00]

	Panel B. Log-returns						
	Time to maturity						
	1 day	1 months	2 month	3 months	4 months	5 months	6 months
Whole period	0.50[0.00]	4.32[0.00]	8.69[0.00]	11.86[0.00]	13.69[0.00]	14.66[0.00]	15.64[0.00]
January	0.59[0.09]	9.07[0.01]	17.74[0.01]	23.36[0.00]	24.73[0.01]	23.57[0.01]	23.96[0.01]
February	0.31[0.08]	4.73[0.22]	14.15[0.02]	22.14[0.01]	26.81[0.00]	27.81[0.01]	26.90[0.02]
March	0.51[0.05]	-0.74[0.77]	4.69[0.48]	12.77[0.10]	18.10[0.04]	21.71[0.04]	23.55[0.06]
April	0.42[0.03]	4.26[0.15]	4.62[0.21]	9.11[0.20]	15.09[0.07]	16.70[0.07]	20.62[0.04]
May	0.34[0.08]	-1.21[0.75]	3.47[0.40]	3.77[0.48]	6.14 0.39]	10.83[0.18]	11.74[0.16]
June	0.32[0.13]	5.71[0.07]	3.92[0.38]	8.14[0.13]	7.50[0.24]	8.14[0.29]	12.22[0.14]
July	-0.23[0.70]	2.56[0.57]	8.69[0.12]	3.74[0.59]	6.46[0.36]	5.24[0.53]	5.71[0.54]
August	0.48[0 .24]	5.77[0.07]	8.96[0.06]	12.41[0.03]	6.73[0.25]	7.99[0.20]	6.74[0.36]
September	0.52[0.11]	-2.17[0.60]	2.88[0.59]	4.35[0.51]	7.89[0.26]	2.82[0.74]	5.63[0.53]
October	1.80[0.01]	12.03[0.04]	12.58[0.13]	15.88[0.07]	17.01[0.07]	19.68[0.05]	15.05[0.15]
November	0.68[0.03]	4.53[0.27]	9.90[0.10]	10.46[0.14]	12.10[0.06]	14.18[0.07]	15.89[0.05]
December	0.24[0.34]	6.93[0.05]	11.77[0.07]	15.31[0.08]	14.74[0.11]	16.10[0.06]	18.07[0.06]
Winter	0.69[0.00]	6.17[0.00]	11.88[0.00]	16.70[0.00]	18.92[0.00]	20.50[0.00]	20.54[0.00]
Summer	0.31[0.03]	2.47[0.09]	5.45[0.00]	6.92[0.00]	8.28[0.00]	8.55[0.01]	10.44[0.00]
Mean equality	1.95[0.05]	1.74[0.08]	2.07[0.04]	2.59[0.01]	2.56 [0.01]	2.58[0.01]	2.00[0.04]
Median Equality	2.88[0.09]	2.49[0.11]	2.25[0.13]	3.39[0.06]	4.38[0.03]	5.35[0.02]	3.04[0.08]
Winter Volatility	13.28	14.73	23.72	27.68	30.00	32.25	35.31
Summer Volatility	13.01	13.63	17.04	22.13	24.64	28.43	30.60
Variance Equality	1.61[0.21]	0.82[0.36]	8.93[0.00]	3.06[0.08]	1.14[0.28]	0.07[0.78]	0.00[0.97]

Table 3. Rollover premiums

In Panel A, rollover premiums are computed as $[F(t-1,t)-S(t)]+\sum_{k=1}^{j-1}\left[F(t-(k+1),t-(k-1))-F(t-k,t-(k-1))\right]$ for j = 3 months, …, 6 months. In Panel B, rollover premiums are computed as $100\times\left[\ln(F(t-1,t)/S(t))+\sum_{k=1}^{j-1}\ln(F(t-(k+1),t-(k-1))/F(t-k,t-(k-1)))\right]$ for j = 3 months, …, 6 months. Other comments are identical to those of Table 2.

	Panel A. Returns.				Panel B. Log-returns			
	Time to maturity				Time to maturity			
	3 months	4 months	5 months	6 months	3 months	4 months	5 months	6 months
Whole period	4.48[0.00]	6.18[0.00]	7.91[0.00]	9.66[0.00]	13.12[0.00]	17.44[0.00]	21.69[0.00]	26.17[0.00]
January	9.21[0.01]	12.26[0.01]	13.10[0.03]	14.37[0.02]	22.58[0.01]	27.95[0.01]	28.51[0.03]	33.56[0.01]
February	9.27[0.02]	10.56[0.01]	13.61[0.01]	14.45[0.02]	22.82[0.01]	27.65[0.01]	33.03[0.01]	33.58[0.02]
March	3.30[0.33]	7.45[0.07]	9.04[0.10]	12.11[0.09]	14.38[0.08]	22.52[0.02]	28.08[0.03]	33.46[0.03]
April	3.01[0.35]	6.32[0.09]	10.47[0.03]	12.06[0.03]	10.05[0.23]	19.75[0.05]	27.88[0.02]	33.44[0.02]
May	0.99[0.58]	3.18[0.36]	6.49[0.11]	10.65[0.04]	3.83[0.49]	9.25[0.31]	18.95[0.07]	27.09[0.02]
June	2.99[0.13]	2.66[0.23]	4.85[0.20]	8.16[0.07]	9.59[0.07]	9.95[0.11]	15.37[0.12]	25.07[0.03]
July	1.84[0.35]	3.41[0.16]	3.07[0.27]	5.27[0.22]	6.89[0.34]	11.72[0.12]	12.08[0.19]	17.50[0.16]
August	4.03[0.02]	4.22[0.05]	5.69[0.02]	5.35[0.05]	15.09[0.02]	13.29[0.05]	16.87[0.02]	17.23[0.04]
September	1.39[0.42]	2.80[0.14]	2.99[0.22]	4.75[0.09]	6.07[0.31]	12.20[0.08]	10.40[0.24]	16.35[0.08]
October	5.14[0.11]	6.67[0.10]	8.08[0.05]	8.27[0.07]	17.63[0.06]	20.82[0.05]	26.95[0.02]	25.15[0.06]
November	4.67[0.25]	5.94[0.17]	7.47[0.16]	8.88[0.09]	10.45[0.18]	15.51[0.07]	18.70[0.07]	24.83[0.02]
December	7.37[0.09]	8.21[0.12]	9.48[0.09]	11.02[0.08]	17.14[0.06]	17.69[0.11]	22.75[0.05]	25.94[0.04]
Winter	6.53[0.00]	8.53[0.00]	10.14[0.00]	11.51[0.00]	17.54[0.00]	22.02[0.00]	26.31[0.00]	29.37[0.00]
Summer	2.38[0.00]	3.76[0.00]	5.56[0.00]	7.71[0.00]	8.61[0.00]	12.69[0.00]	16.85[0.00]	22.78[0.00]
Mean equality	2.56[0.01]	2.44[0.01]	1.93[0.06]	1.39[0.16]	2.24[0.03]	1.98[0.04]	1.69[0.09]	1.04[0.30]
Median equality	2.71[0.09]	2.77[0.09]	1.83[0.18]	0.57[0.44]	2.36[0.12]	1.69[0.09]	2.07[0.15]	0.75[0.38]
Winter volatility	13.19	15.49	18.40	20.61	29.16	34.60	40.24	45.13
Summer volatility	7.47	9.45	12.14	14.41	23.10	27.23	32.98	37.82
Variance equality	15.31[0.00]	11.32[0.00]	7.19[0.00]	6.18[0.01]	3.94[0.04]	1.56[0.21]	1.07[0.30]	0.66[0.41]

Table 4. Liquidity premiums

Liquidity premiums are computed as the difference between the rollover and the risk premiums for *j* = 3 months, …, 6 months obtained in Tables 2 and 3. Other comments are identical to those of Table 2 and Table 3.

	Panel A. Returns.				Panel B. Log-returns			
	Time to maturity				Time to maturity			
	3 months	4 months	5 months	6 months	3 months	4 months	5 months	6 months
Whole period	0.24[0.18]	1.09[0.00]	2.28[0.00]	3.52[0.00]	1.26[0.00]	3.75[0.00]	7.03[0.00]	10.54[0.00]
January	-1.14[0.25]	0.17[0.82]	0.67[0.71]	2.03[0.25]	-0.79[0.68]	3.22[0.14]	4.93[0.29]	9.60[0.05]
February	0.33[0.15]	-0.31[0.73]	1.28[0.15]	1.59[0.41]	0.67[0.29]	0.85[0.69]	5.22[0.07]	6.68[0.19]
March	0.73[0.17]	2.38[0.02]	2.72[0.07]	3.97[0.03]	1.61[0.25]	4.42[0.06]	6.37[0.07]	9.91[0.03]
April	0.56[0.56]	2.12[0.05]	6.02[0.02]	5.97[0.02]	0.95[0.68]	4.66[0.10]	11.19[0.00]	12.82[0.02]
May	-0.12[0.80]	1.35[0.36]	3.30[0.04]	7.53[0.01]	0.05[0.96]	3.12[0.32]	8.12[0.04]	15.35[0.00]
June	0.40[0.03]	0.62[0.27]	2.66[0.12]	4.91[0.02]	1.44[0.10]	2.45[0.09]	7.24[0.05]	12.85[0.01]
July	0.95[0.09]	1.77[0.01]	2.23[0.02]	4.29[0.03]	3.15[0.04]	5.26[0.01]	6.84[0.00]	11.80[0.01]
August	0.63[0.06]	1.88[0.02]	2.79[0.00]	3.39[0.01]	2.68[0.03]	6.57[0.00]	8.87[0.00]	10.49[0.00]
September	0.45[0.25]	1.10[0.10]	2.14[0.03]	3.30[0.01]	1.72[0.14]	4.30[0.02]	7.58[0.00]	10.71[0.00]
October	0.48[0.59]	1.19[0.32]	1.78[0.26]	3.11[0.10]	1.74[0.35]	3.81[0.14]	7.27[0.04]	10.11[0.02]
November	-0.54[0.50]	0.60[0.60]	0.69[0.67]	1.36[0.53]	-0.01[1.00]	3.40[0.17]	4.52[0.22]	8.93[0.05]
December	0.19[0.76]	0.42[0.77]	1.51[0.26]	1.34[0.43]	1.83[0.15]	2.96[0.38]	6.64[0.06]	7.87[0.07]
Winter	-0.00[1.00]	0.72[0.09]	1.43[0.01]	2.21[0.00]	0.84[0.17]	3.10[0.00]	5.82[0.00]	8.84[0.00]
Summer	0.49[0.02]	1.47[0.00]	3.18[0.00]	4.90[0.00]	1.70[0.00]	4.42[0.00]	8.30[0.00]	12.34[0.00]
Mean equality	-1.37[0.17]	-1.36[0.18]	-2.18[0.03]	-2.59[0.01]	-1.06[0.29]	-1.03[0.31]	-1.41[0.16]	-1.55[0.12]
Median equality	3.98[0.04]	5.32[0.02]	9.81[0.00]	10.60[0.00]	2.30[0.13]	2.88[0.09]	4.74[0.03]	3.07[0.08]
Winter volatility	2.71	4.03	5.41	6.79	5.74	9.18	12.87	15.91
Summer volatility	1.94	3.20	5.18	6.84	5.05	7.75	10.03	13.70
Variance equality	3.98[0.04]	2.70[0.10]	0.82[0.36]	0.02[0.92]	1.87[0.17]	2.56[0.11]	4.32[0.04]	1.40[0.24]

Table 5. Volatility and skewness of system average price

The standard deviation and the skewness coefficients for the daily system average price are computed within each month in the sample using returns and log-returns in Panel A and B, respectively. Other comments are identical to those of Table 2.

	Panel A. Returns		Panel B. Log-returns	
	Volatility	Skewness	Volatility	Skewness
Whole period	3.00 [0.00]	0.11 [0.05]	12.73 [0.00]	-0.32 [0.00]
January	3.28 [0.00]	0.48 [0.14]	11.10 [0.00]	0.28 [0.33]
February	3.24 [0.00]	-0.29 [0.05]	12.72 [0.00]	0.61 [0.00]
March	5.14 [0.03]	0.00 [0.99]	13.43 [0.00]	0.07 [0.78]
April	2.08 [0.00]	0.36 [0.16]	9.07 [0.00]	-0.05 [0.80]
May	2.31 [0.00]	0.10 [0.41]	10.65 [0.00]	-0.43 [0.05]
June	2.22 [0.00]	0.13 [0.47]	9.22 [0.00]	-0.32 [0.23]
July	2.22 [0.00]	-0.07 [0.49]	12.15 [0.00]	-0.42 [0.06]
August	2.10 [0.00]	-0.20 [0.24]	11.18 [0.00]	-0.45 [0.03]
September	3.00 [0.00]	0.18 [0.42]	15.44 [0.00]	-0.64 [0.01]
October	3.87 [0.00]	0.34 [0.08]	22.18 [0.00]	-1.29 [0.00]
November	3.26 [0.00]	0.21 [0.22]	13.52 [0.00]	-0.77 [0.00]
December	3.47 [0.00]	0.09 [0.70]	12.14 [0.00]	-0.43 [0.19]
Winter	3.70 [0.00]	0.14 [0.12]	14.19 [0.00]	-0.26 [0.03]
Summer	2.32 [0.00]	0.08 [0.25]	11.29 [0.00]	-0.39 [0.00]
Mean equality	3.21[0.00]	0.48[0.62]	1.90[0.05]	0.87[0.38]
Median equality	3.18[0.00]	0.42[0.66]	1.03[0.31]	0.88[0.35]

Table 6. Regression of risk premiums on explicative variables

This table reports the estimation results of the following regression

$$F(t-j,t)-S(t)=a+bSD(t-j)+cUWD(t-j)+dDUK(t-j)+\varepsilon(t-j,t)$$

for j = 1 *day*, 1, 2, 3, 4, 5 and 6 months to delivery. *SD* refer to the standard deviation within each month of the daily system average price. *UWD* represents for winter months the UHDD product with DUK when DUK is negative. The UHDD variable measures the difference between the historical value and the observed daily-accrued heating degree-day for each month within the year for the United Kingdom. *DUK* refers to the natural gas reservoirs levels changes in the United Kingdom. Significance of the coefficients at the 1%, 5% and 10% levels are indicated with one (*), two (**) and three (***) asterisks, respectively; based on the *t*-statistics computed with the Newey-West consistent estimators. For the day-ahead forwards the dependent variable is computed in each month as the average value of $F(t-1\,day,t)-S(t)$. The data period goes from April 2000 to February 2015.

Time to delivery	*a*	*SD*	$UWD\times10^5$	$DUK\times10^3$	R^2(%)
1 day	-0.33*	0.17*	1.05*	-1.67	49.89
1 month	-0.95	0.46*	6.06**	-0.17	17.90
2 months	-0.17	0.67*	12.81*	-1.19	22.09
3 months	0.64	0.84*	14.29*	-2.44**	19.89
4 months	1.77	0.76*	12.87**	-3.98*	15.31
5 months	1.96***	0.84*	13.04**	-5.08*	14.26
6 months	2.18***	0.90*	1.29**	-5.25*	12.21

Table 7. Regression of rollover premiums on explicative variables

This table shows the estimation results of the regression

$$ROP(t-j,t) = a + bSD(t-j) + cUWD(t-j) + dDUK(t-j) + \varepsilon(t-j,t)$$

for j = 3, 4, 5 and 6 months to maturity. Realized rollover premiums from $t-j$ until t are computed as follows

$$ROP(t-j,t) = (F(t-1,t) - S(t)) + \sum_{k=2}^{j}(F(t-k-1,t-k) - F(t-k,t-k))$$

for j = 3, 4, 5 and 6 months. Other comments are identical to those of Table 6.

Time to delivery	a	SD	$UWD \times 10^5$	$DUK \times 10^3$	R^2(%)
3 months	0.71	0.88*	13.68*	-1.62	19.44
4 months	2.22***	0.91*	1.38**	-3.06**	15.22
5 months	2.66***	1.21*	1.74**	-4.15**	17.04
6 months	3.67**	1.38*	1.72**	-4.23**	15.46

Table 8. Regression of the difference between the rollover and risk premiums on explicative variables

This table shows the estimation results of the following regression

$$ROP(t-j,t)-\left[F(t-j,t)-S(t)\right]=a+bSD(t-j)+cUWD(t-j)+dDUK(t-j)+eOI(t-j)+\varepsilon(t-j,t)$$

for j = 3, 4, 5 and 6 months to maturity. *OI* refer to the monthly average of the daily open interest of each futures contract. Other comments are identical to those of Table 6 and 7.

Time to delivery	a	SD	$UWD\times10^5$	$DUK\times10^4$	$OI\times10^4$	R^2(%)
3 months	0.31	0.03	-0.64	8.15***	-0.24	5.92
4 months	1.12**	0.13*	0.83	9.94*	-0.72**	8.52
5 months	1.50***	0.34**	4.16***	11.01***	-0.97**	15.94
6 months	2.45**	0.45***	3.93***	12.30	-1.32**	14.41

Table 9. Transaction costs.

Bid and ask prices are taken at hourly frequencies from 23 October 2014, until 23 October 2015 (2560 hourly observations). The relative bid-ask spreads obtained over the average between bid and ask prices. Fees are extracted from ICE rules in May 2014, the total member trading fees for a contract would be £1.90 for NBP monthly contracts (about 0.003% of the underlying value).

	Roll-over			*Single trade*			
Time to delivery	*fees*	*Bid-ask*	*Total*	*fees*	*Bid-ask*	*Total*	*Difference*
1 month	0.003%	0.17%	0.173%	0.003%	0.17%	0.173%	–
2 months	0.003%	0.17%	0.173%	0.003%	0.17%	0.173%	–
3 months	0.006%	0.34%	0.346%	0.003%	0.23%	0.233%	0.113%
4 months	0.009%	0.51%	0.519%	0.003%	0.36%	0.363%	0.156%
5 months	0.012%	0.68%	0.692%	0.003%	0.50%	0.503%	0.189%
6 months	0.015%	0.83%	0.845%	0.003%	0.89%	0.893%	-0.048%

Annex II: Figures

Figure 1. Monthly average traded volume and open interest

These figures show the monthly average traded volume and open interest. M1 to M12 are used to indicate the contracts with 1 month to 12 months left until maturity of monthly futures contracts.

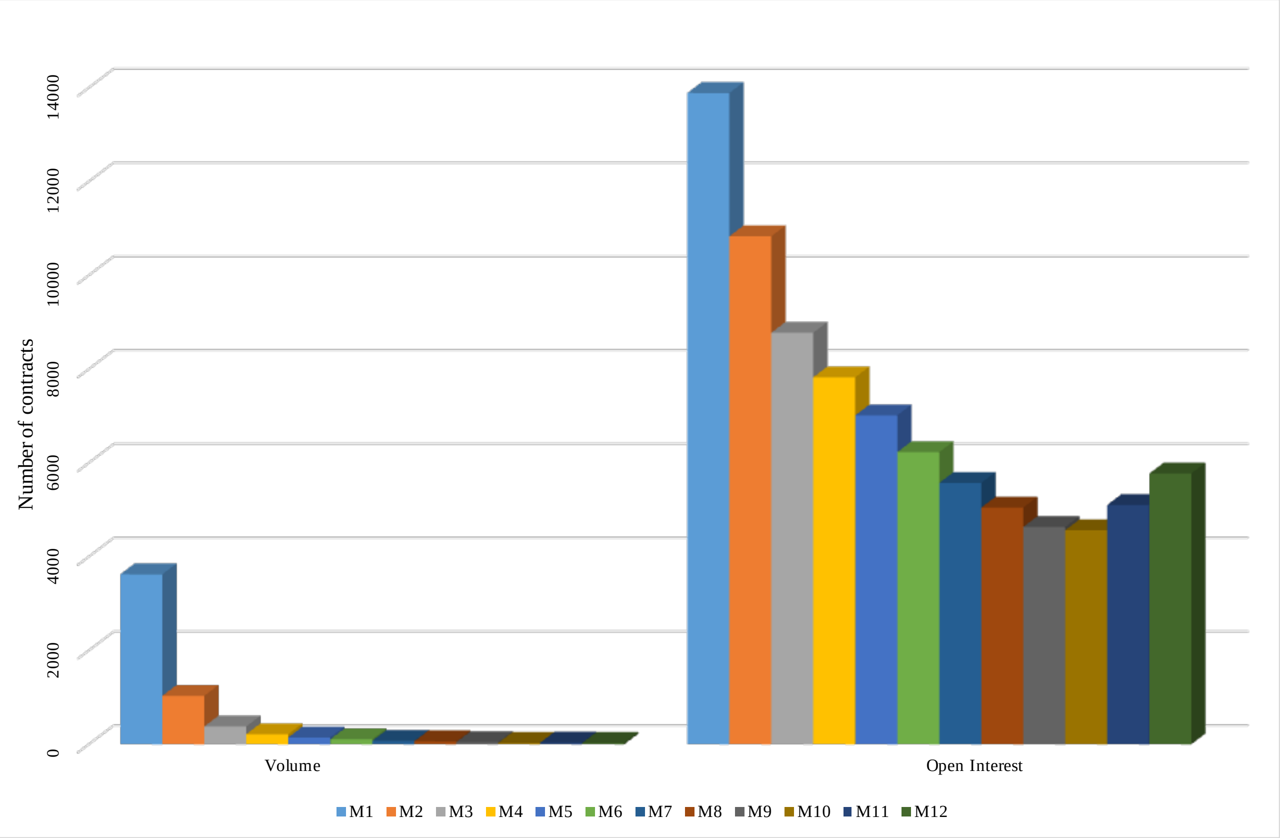


Figure 1(a). These figures show the total average monthly traded volume (left) and total average monthly open interest (right).

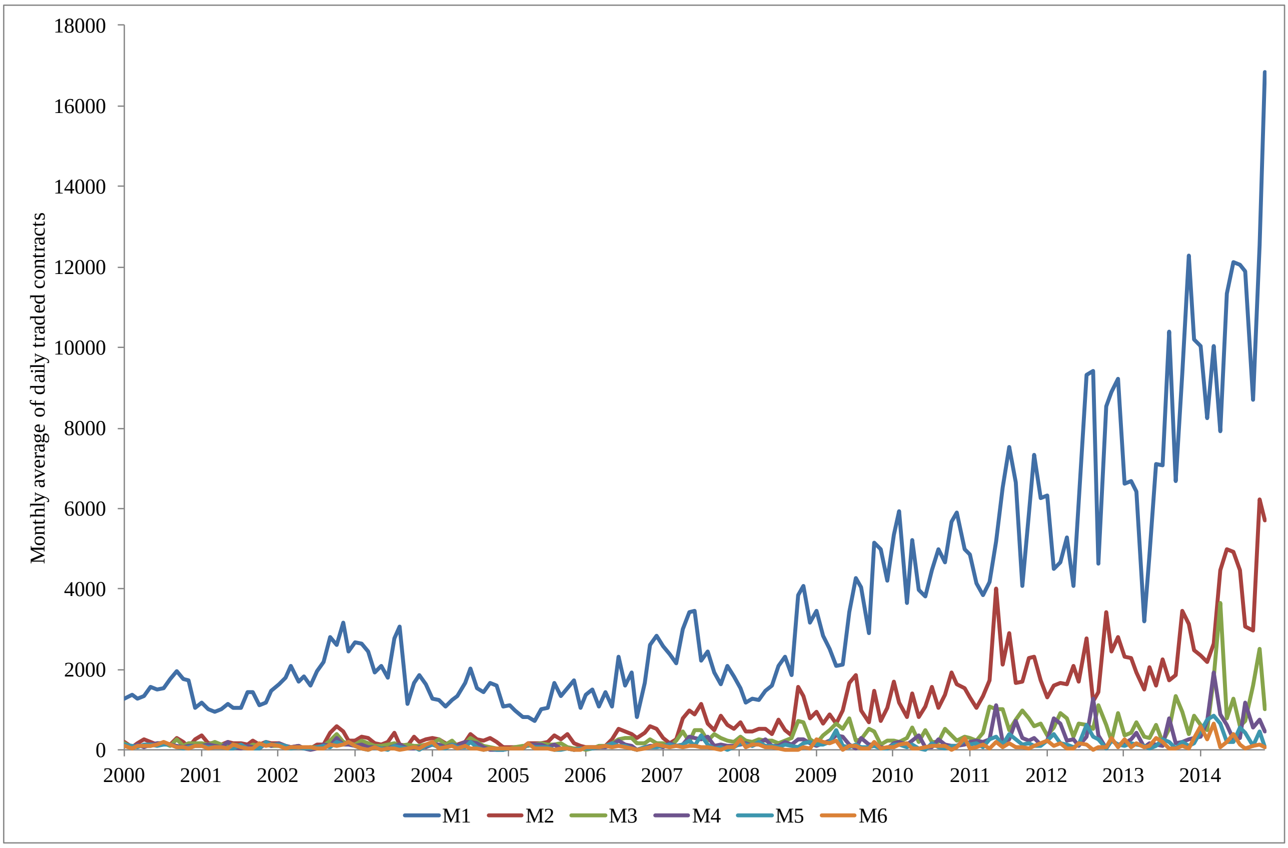


Figure 1(b). This figure shows the monthly average traded volume time series for contracts with 1 month to 6 months left until maturity.

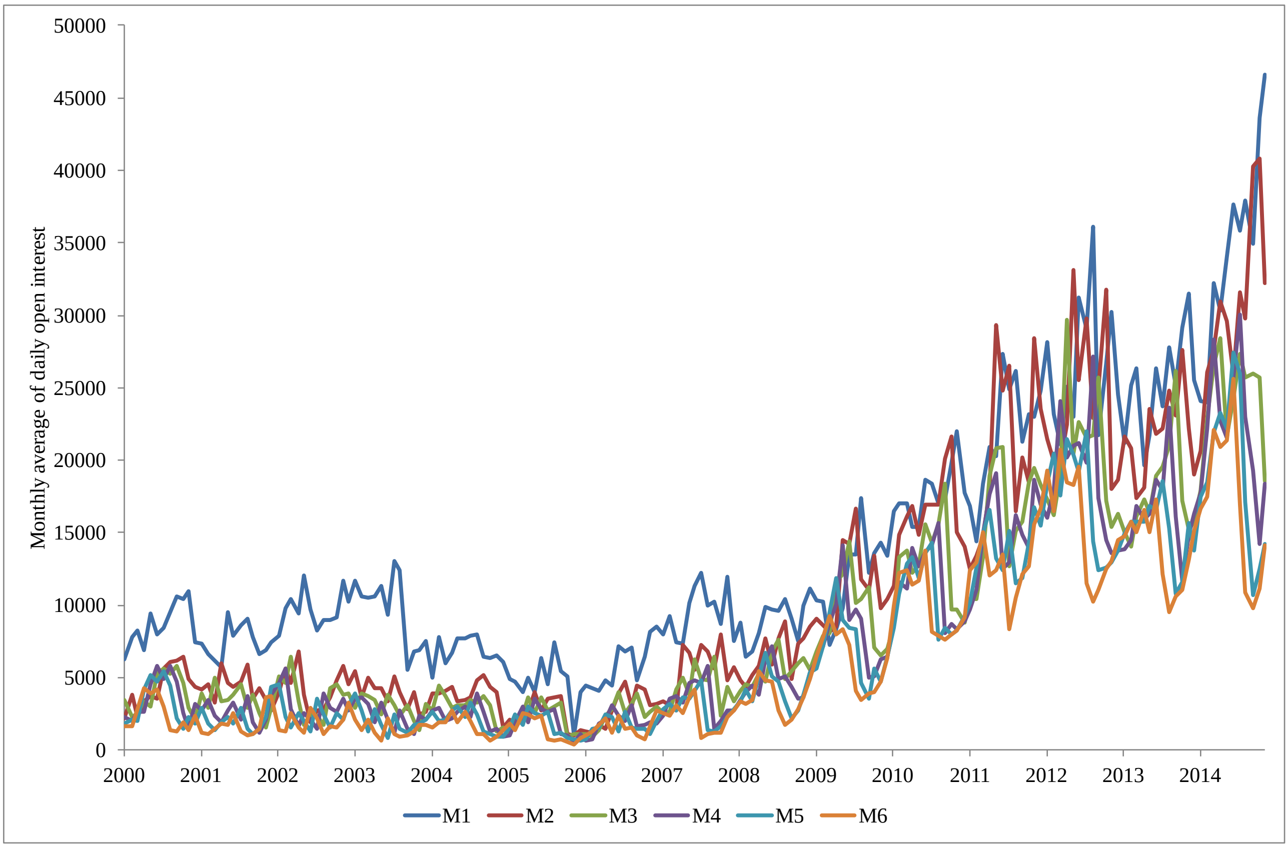


Figure 1(c). This figure shows the monthly average open interest time series for contracts with 1 month to 6 months left until maturity.

Figure 2. Heating degree days in the United Kingdom

This figure shows the monthly heating degree days in the dashed line (-----) and its historical average value for each month in the continuous line (──). Historical average value is computed using the heating degree days since 1974 until the year prior to the current year.

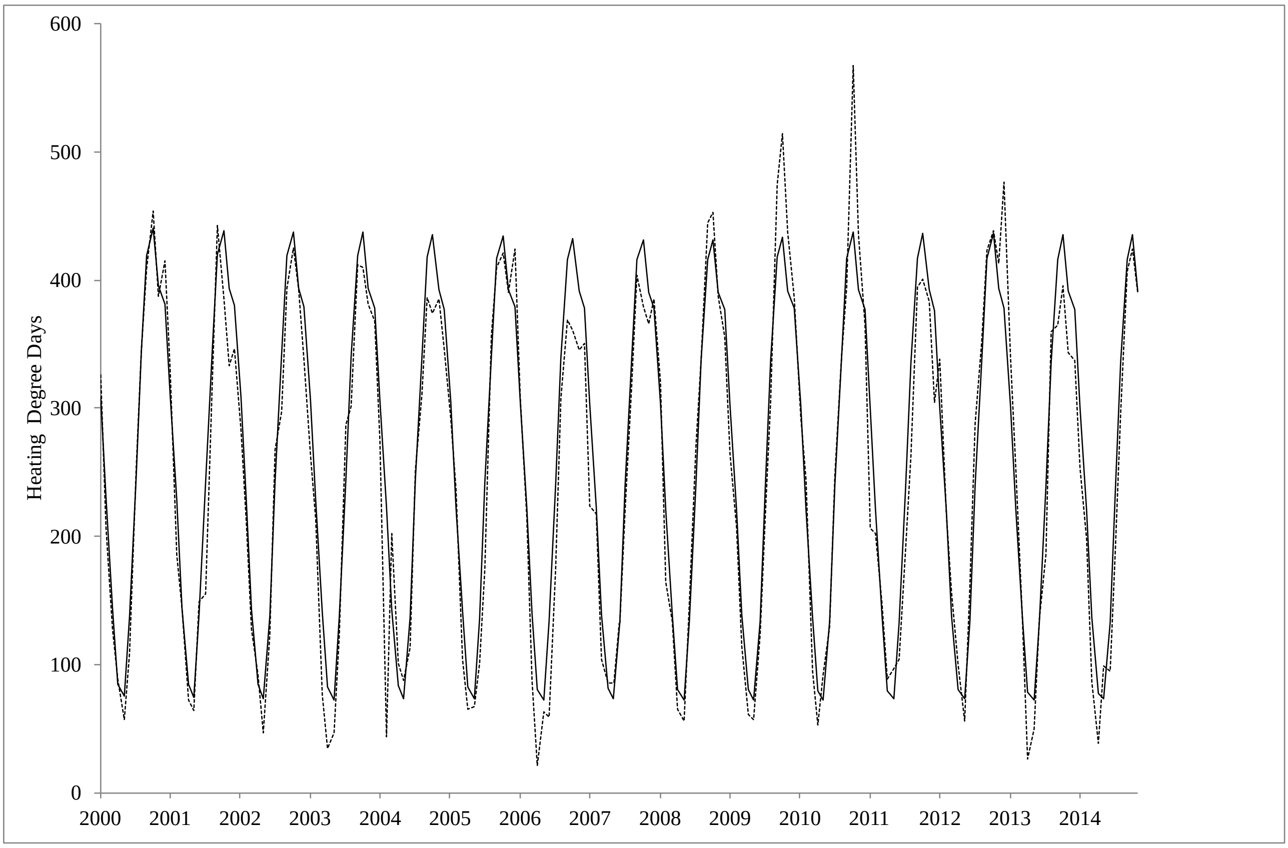


Figure 3. Natural gas storage levels

This figure reports the monthly natural gas storage levels in the United Kingdom.

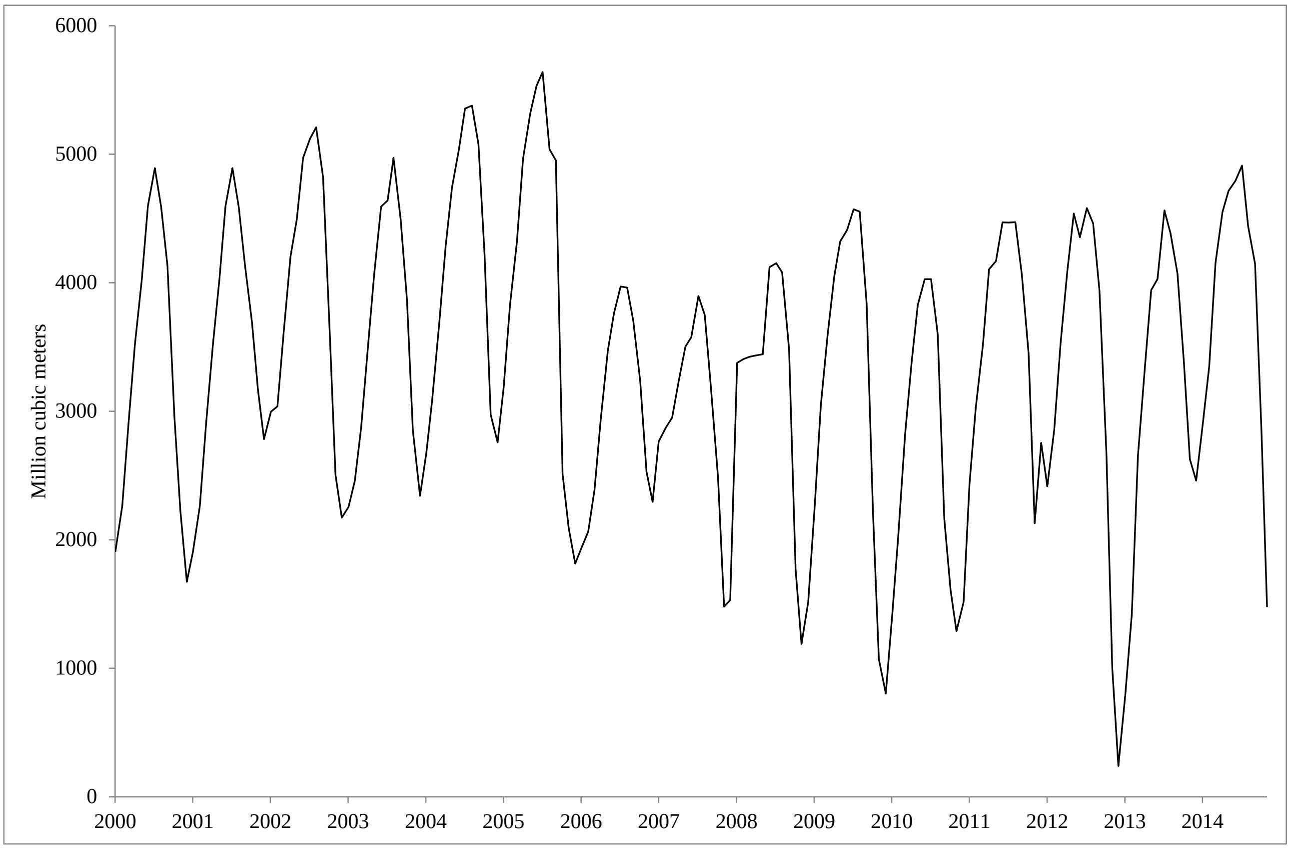


Figure 4: Day-ahead monthly average price, monthly system average price and the monthly average risk premium between the previous two

Day-ahead monthly average price (------), Monthly system average price (——) and the monthly average risk premium (·······) contained in day-ahead prices computed as the difference between the previous two.

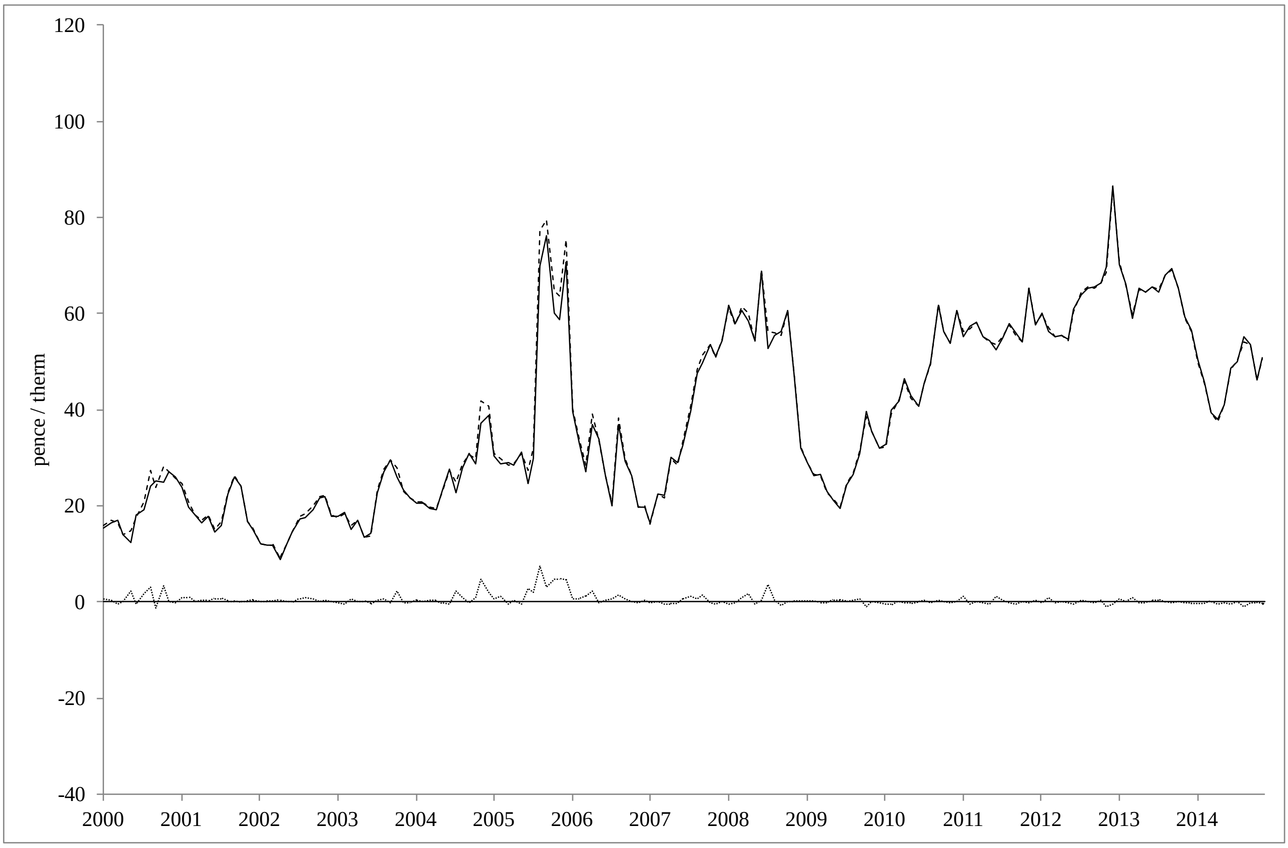


Figure 5: Futures front contract price, monthly system average price and the ex post risk premium

Futures front contract price ($F(t\text{–}1,t)$) on the day prior to maturity (------); monthly system average Price ($S(t)$) (——); and the *ex post* observed risk premium in 't' (·······) computed as $F(t\text{–}1,t) - S(t)$.

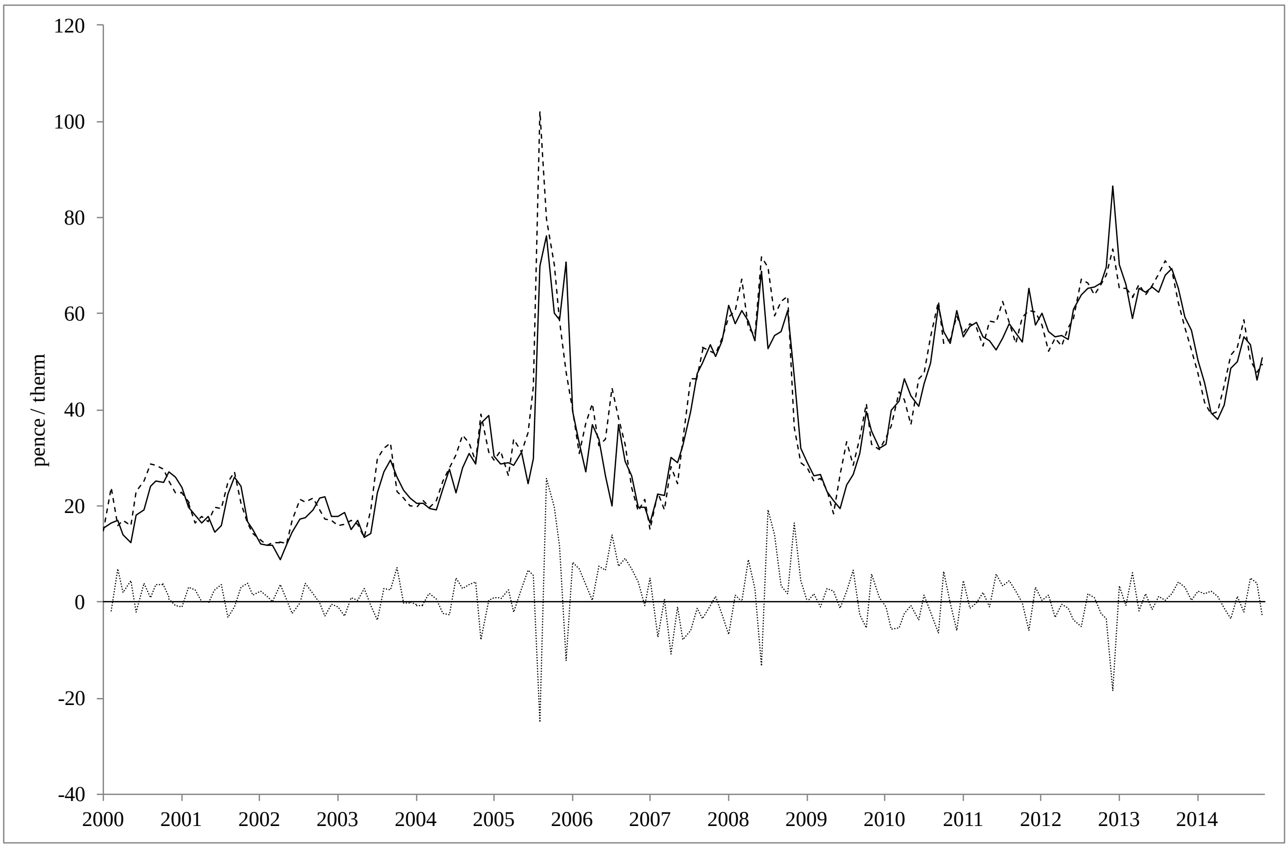


Figure 6: Second to maturity futures contract, monthly system average price and ex post risk premium

Second to maturity futures contract price ($F(t–2,t)$) (------), monthly system average price ($S(t)$) (——), and the *ex post* observed risk premium in 't' (·······) computed as $F(t–2,t) – S(t)$.

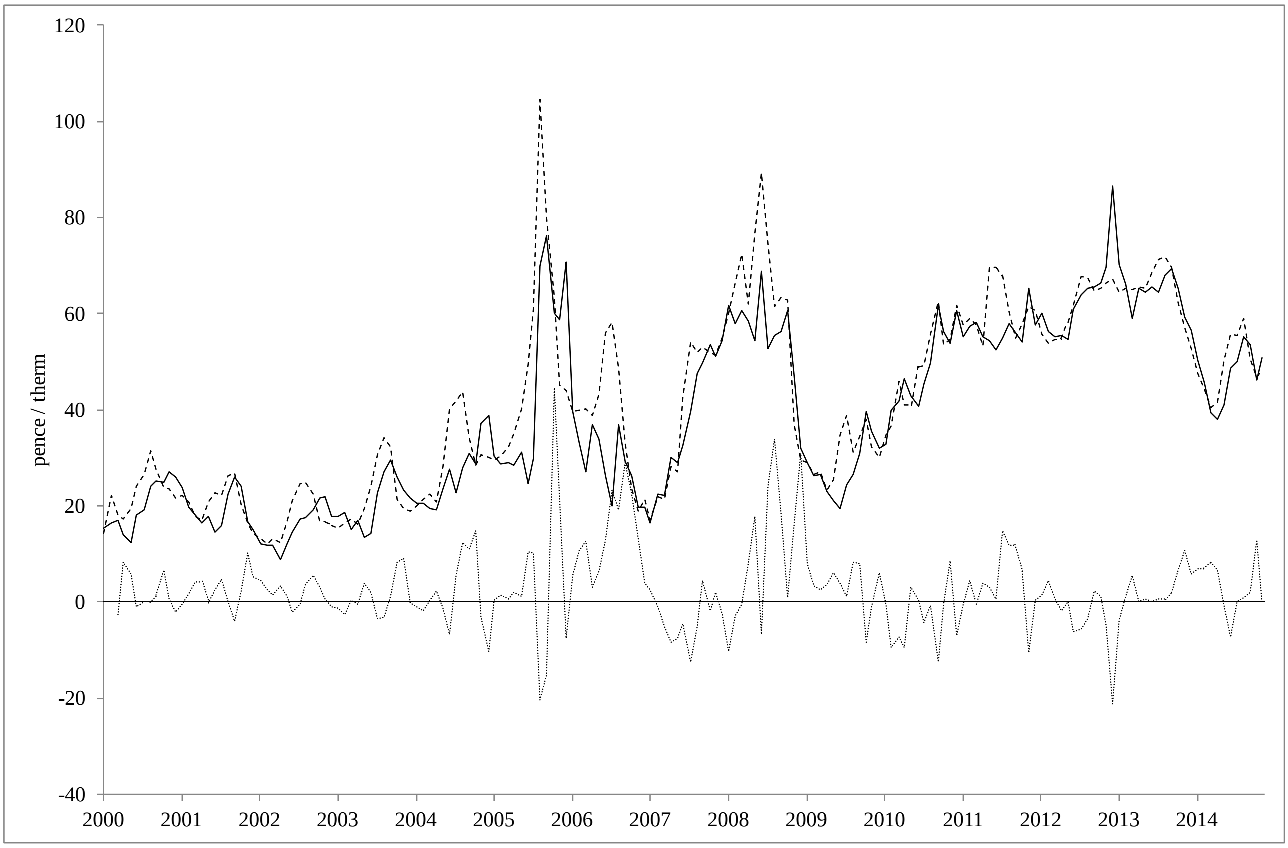


Figure 7: Ex post and rollover risk premiums

Ex post risk premiums (------) computed as $F(t{-}j,t) - S(t)$, for j = 3, 4, 5 and 6 months; and rollover premiums (——) computed as $[F(t-1,t)-S(t)]+\sum_{k=1}^{j-1}\left[F(t-(k+1),t-(k-1))-F(t-k,t-(k-1))\right]$ for j = 3, 4, 5 and 6 months.

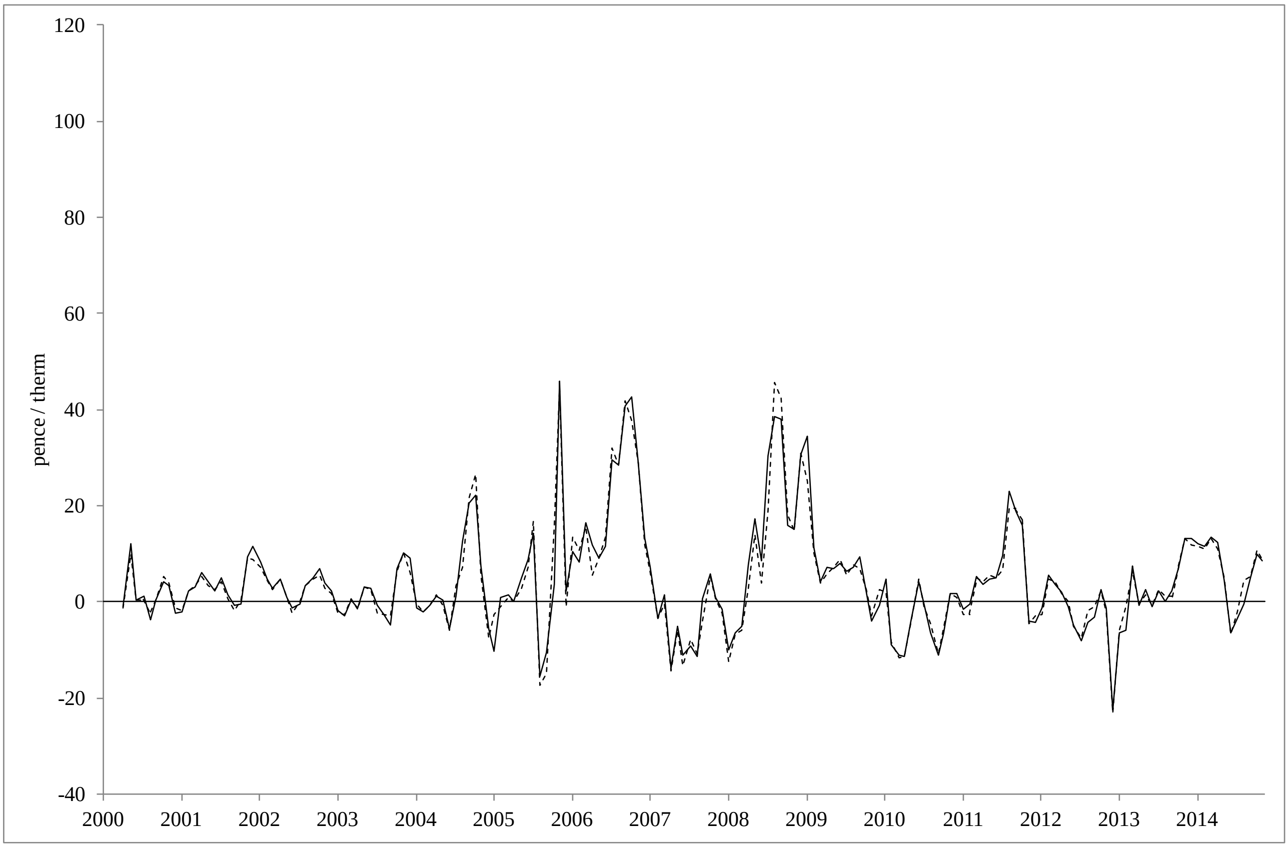


Figure 7(a). Three months prior to delivery.

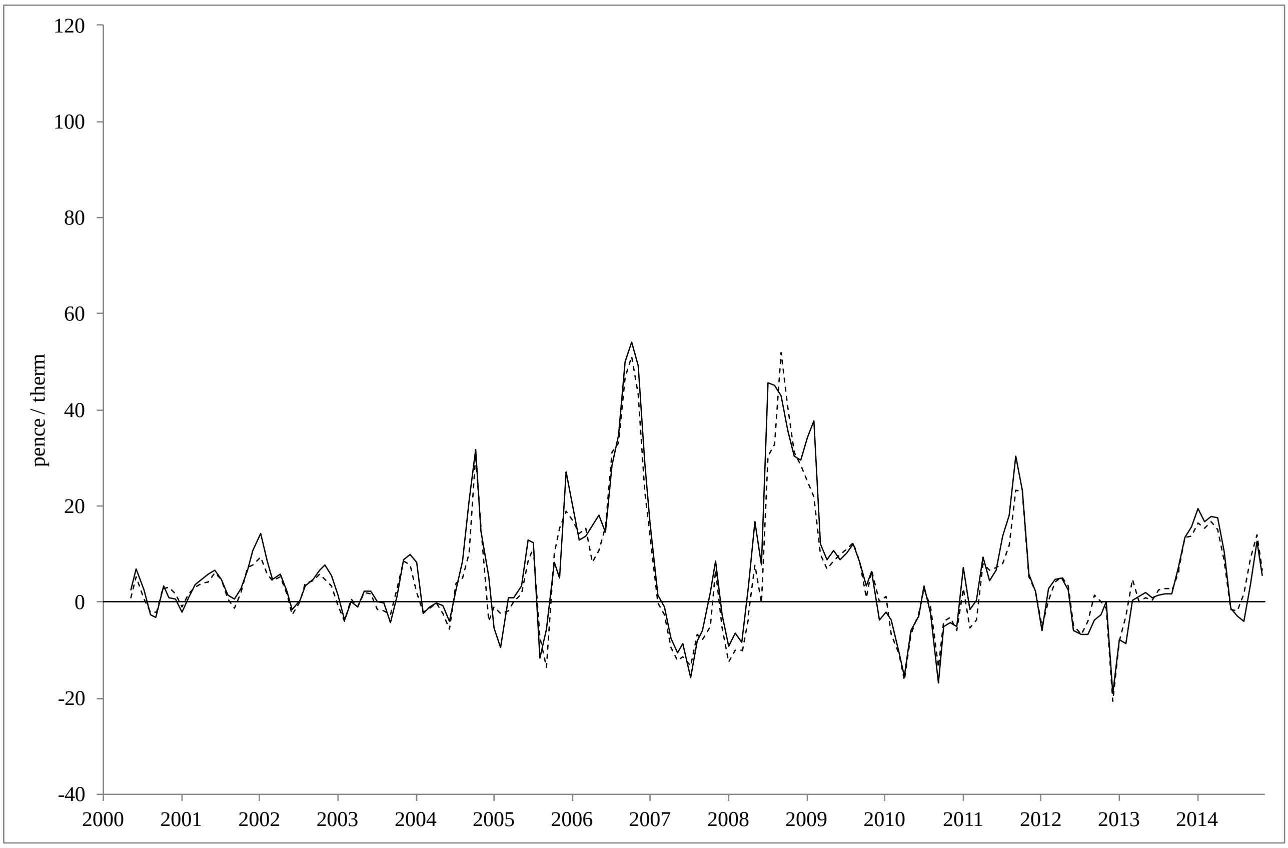


Figure 7(b). Four months prior to delivery.

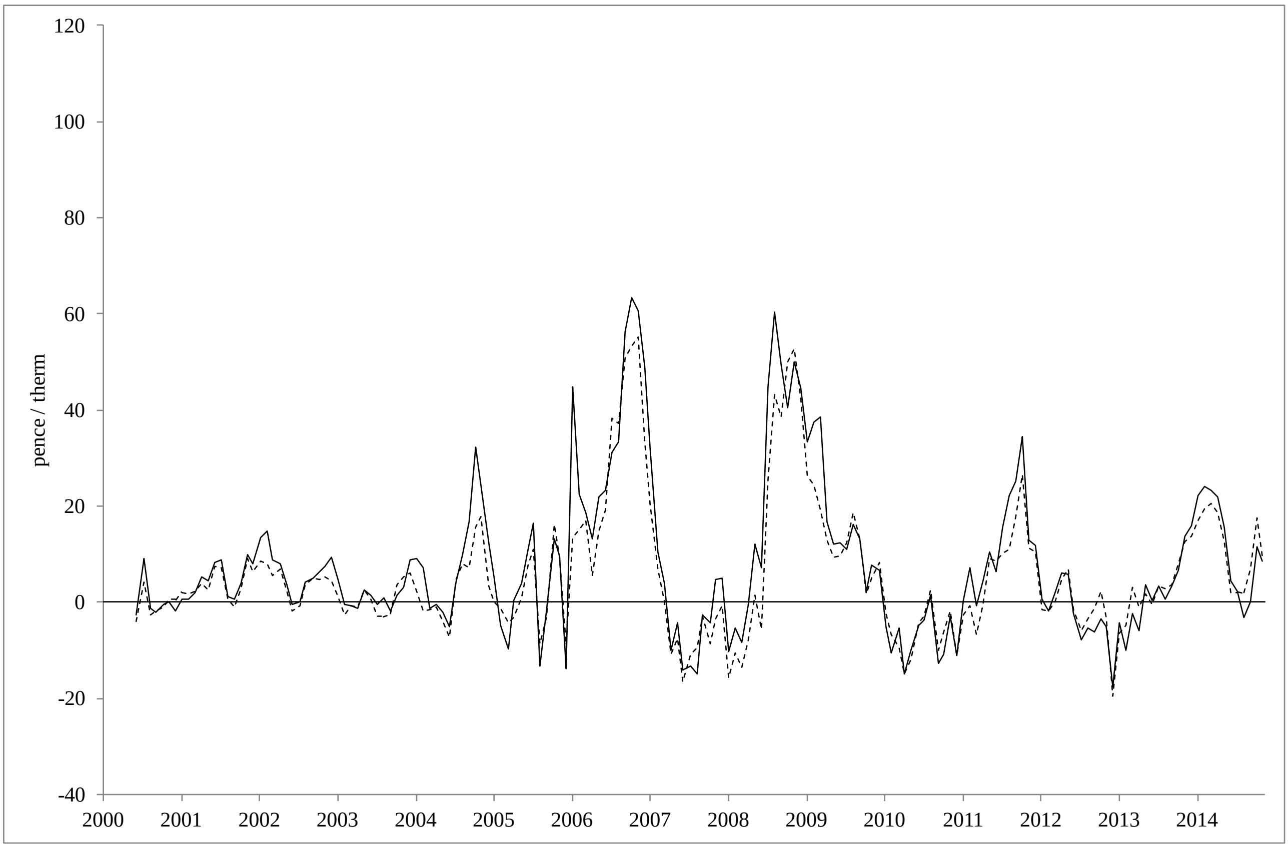


Figure 7(c). Five months prior to delivery.

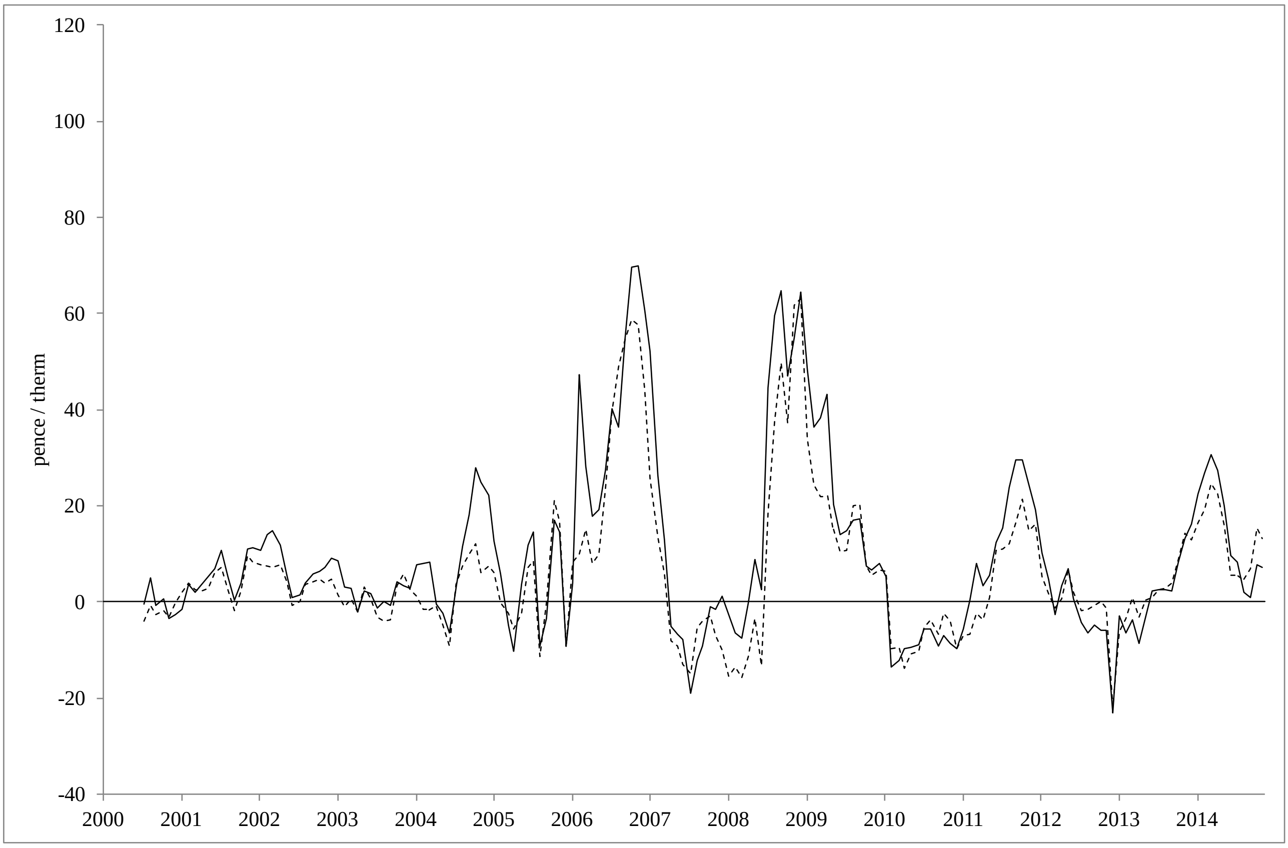
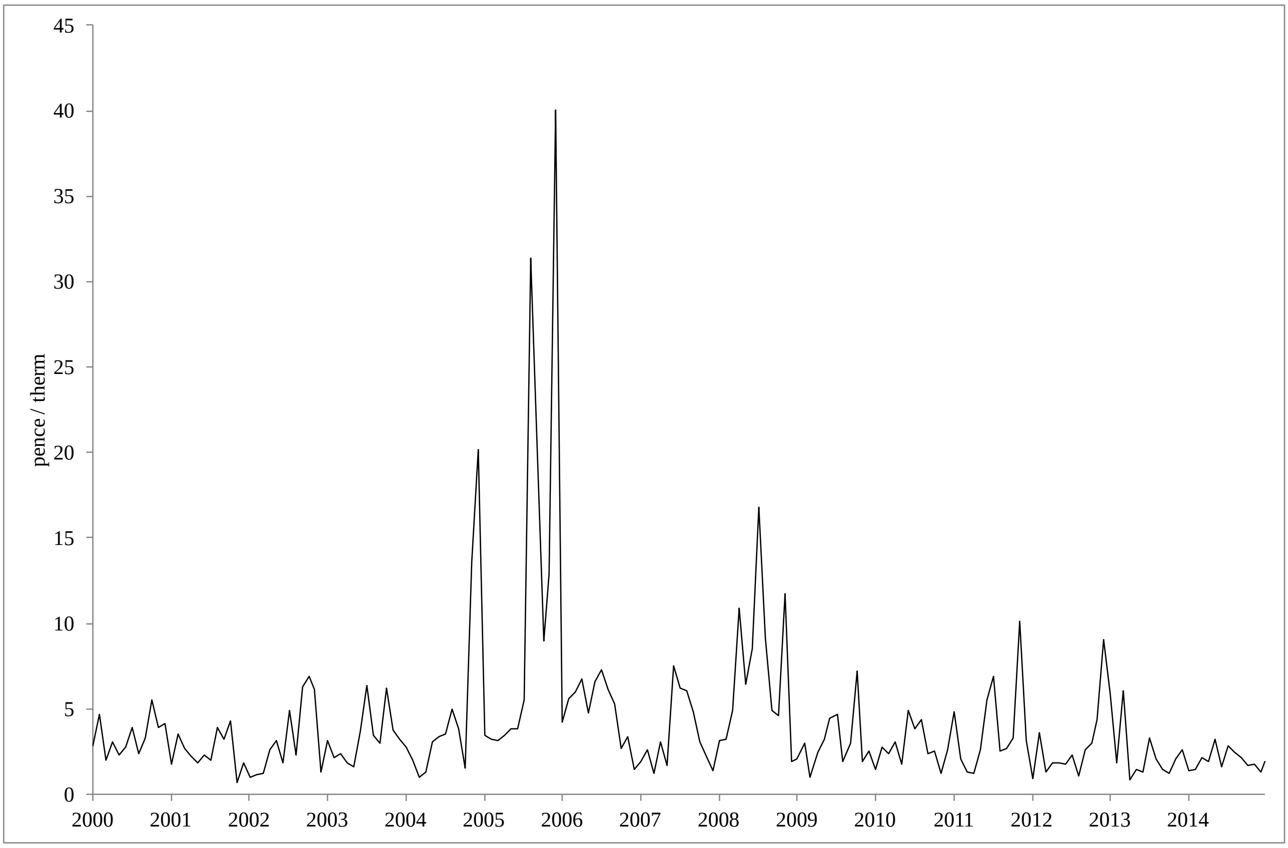


Figure 7(d). Six months prior to delivery.

Figure 8. Volatility of the system average price

The standard deviation of the system average price for each month in the sample.



Appendix

Table A1. Regression of convenience yield on explicative variables

This table reports the estimation results of the following regression

$$CY(t-j,t) = a + bSD(t-j) + cUWD(t-j) + dDUK(t-j) + \varepsilon(t-j,t)$$

where $CY(t-j,t)$ represents the convenience yield for a futures contract j days or months before its maturity in t. A proxy of the convenience yield is computed following Wei and Zhu (2006) as

$$CY(t-j,t) = \left(1 + R(t-j,t) \times \frac{j}{360}\right) \times S(t-j) - F(t-j,t)$$

where $R(t-j,t)$ is the monthly average rate of the LIBOR for j days (30, 60, …,180 days) and the monthly average of the SONIA (Sterling Overnight Interest Average) for the day-ahead ($j = 1$). These rates are retrieved from the Bank of England website. For more details, please, see Table 6 in the paper.

Time to delivery	a	SD	$UWD\times10^5$	$DUK\times10^3$	R^2(%)
1 day	0.47*	-0.15*	-0.79**	0.02	41.96
1 month	4.35*	0.59*	3.84	-0.87	12.78
2 months	9.01*	0.94*	7.64	-3.68***	12.97
3 months	14.33*	1.49**	14.69**	-8.59*	16.04
4 months	14.63*	1.87***	15.65**	-12.71*	16.02
5 months	43.11*	1.91***	28.31**	-18.94*	8.26
6 months	46.83*	-0.21	28.08**	-19.55*	8.58

Table A2. Regression of risk premiums on explicative variables and the convenience yield

This table reports the estimation results of the following regression.

$$F(t-j,t) - S(t) = a + bSD(t-j) + cUWD(t-j) + dDUK(t-j) + eCY(t-j,t) + \varepsilon(t-j,t)$$

For more details, please, see Table 6 in the paper and the previous Table A1.

Time to delivery	a	SD	$UWD\times10^5$	$DUK\times10^3$	CY	R^2(%)
1 month	-0.39	0.54*	6.56**	0.01	-0.12***	21.02
2 months	1.11	0.81*	0.14*	-1.71***	-0.14*	27.35
3 months	2.13**	0.99*	0.16*	-3.33*	-0.10*	23.95
4 months	3.13*	0.87*	0.14**	5.16*	-0.09**	18.22
5 months	4.37*	0.88*	0.15**	6.14*	-0.06*	17.36
6 months	4.84*	0.89*	0.15**	6.36*	-0.06**	14.88

Table A3. Regression of rollover premiums on explicative variables and the convenience yield

This table shows the estimation results of the regression.

$$ROP(t-j,t) = a + bSD(t-j) + cUWD(t-j) + dDUK(t-j) + eCY(t-j,t) + \varepsilon(t-j,t)$$

Other comments are identical to those of Tables 6, 7, A1 and A2.

Time to delivery	*a*	*SD*	*UWD*×10^5	*DUK*×10^3	*CY*	R^2(%)
3 months	1.90***	1.00*	14.90**	-2.34**	-0.08**	22.02
4 months	3.10**	0.99*	14.80**	-3.83**	-0.06	16.26
5 months	3.99**	1.24*	18.28*	-4.74**	-0.03	17.74
6 months	4.98**	1.38*	17.97**	-4.78**	-0.03	15.91

Table A4. Regression of the difference between the rollover and risk premiums on explicative variables and the convenience yield

This table shows the estimation results of the following regression.

$$\begin{aligned} ROP(t-j,t) - [F(t-j,t) - S(t)] \\ &= a + bSD(t-j) + cUWD(t-j) + dDUK(t-j) + eOI(t-j) + fCY(t-j,t) \\ &+ \varepsilon(t-j,t) \end{aligned}$$

Other comments are identical to those of Tables 6, 7, 8, A1, A2 and A3.

Time to delivery	*a*	*SD*	*UWD*×10^5	*DUK*×10^4	*OI*×10^4	*CY*	R^2(%)
3 months	-0.25	0.01	0.11	-0.91	9.97**	0.02**	8.75
4 months	0.37	0.11*	-3.55	0.47	0.01*	0.03***	10.93
5 months	-0.07	0.35**	-2.72	3.65	0.01**	0.02***	18.68
6 months	0.59	0.47***	-4.47	3.41	0.01**	0.03***	16.49

Chapter III

HEDGING SPARK SPREAD RISK WITH FUTURES

1. Introduction

In the transition path to 'low greenhouse gas emissions development' under the Paris Agreement, the decarbonisation of the electricity sector is a central factor. To meet this target, the energy sector needs to begin a transition process to a less contaminant future in which gas acts as a 'bridge fuel' to a low-carbon power generation system (Peters, 2017). The European Commission has agreed ambitious targets to reduce CO_2 emissions by more than 40% (80%) by 2030 (2050) as compared to 1990 levels; and to increase the share of low carbon technologies in the electricity mix from approximately 45% today to nearly 100% by 2050, when renewable energy sources will represent more than 50% (Boie et al., 2014). In addition to the target of reducing CO_2 emissions, another goal of EU energy policy is the security of supply. For meeting greenhouse gas emissions reductions and peaking electricity demand at times of low renewable energy supply, natural gas is the backup energy source because natural gas fired generation can rapidly ramp output in response to variable output from renewable sources – particularly solar and wind (Pless et al., 2016).

The deregulation of energy markets initiated in the 1990s has led to competition and price uncertainty in many countries. In the case of an energy market agent whose payoffs depend simultaneously on electricity and natural gas prices, this uncertainty is doubled. The spark spread can be defined as the gross profit margin earned by buying and burning natural gas to produce electricity. The size of this profit depends on energy prices and generator efficiency. The clean spark spread reduces the spark spread with the cost of emitting CO_2 to the atmosphere. Further to the spark and clean spark spreads, the range of the energy and commodities spreads family is quite wide: quark (nuclear to electricity); dark (coal to electricity); clean dark (coal to electricity and CO_2); crack (oil to gasoline and heating oil); and crunch (soy bean to soy oil and soy meal). In many cases, these spreads can be traded in a closed combination of futures contracts bought and sold in the market.

Following Emery and Liu (2002), the spark spread became available when the NYMEX initiated trading in electricity futures in March 1996 and remained possible until 2002. However, in May

2002 electricity contracts on Nymex became over-the-counter (OTC), and so spark spreads had to also become OTC on NYMEX. Spark spreads have also started OTC trading in Europe. The spark spread forward curve is very important to energy industry planners as it provides a method for electricity producers to lock in generation profits. The forward curve of the spark spread and its average values can indicate to gas-fired generation companies how to maximise profits in their forward trading by choosing maturities with higher spreads. The spark spread can also help regulators monitor if electricity forward prices are directly influenced by gas prices, and in case of remarkable divergences, help reveal if a market anomaly has occurred (Capitan and Rodriguez, 2013).

As Borovkova and Geman (2006) remarked, in the energy industry, inter-commodity spreads are as important as prices. In this paper, we deal with several important issues related to the joint risk management of electricity and natural gas prices. Our approach for futures hedging will be useful to those agents involved in the simplest tolling agreement who want to reduce uncertainty on payoffs.[1] That is, a contract in which the payoffs are computed as the spark spread. Such agents will be interested in studying the alternative of trading in the spot market: the spark spread being a proxy of its payoffs. Risk management of these contracts can be improved using futures contracts. There are several papers on electricity and natural gas price risk management, but no paper has attempted to simultaneously determine the optimal position in futures on electricity and natural gas to hedge spark spread risk (see for example Torró, 2011, and Martinez and Torró, 2015). We show that clean spark spread risk and spark spread risk are two indistinguishable variables for futures hedging purposes. Therefore, this paper looks for the simultaneous optimal futures hedging positions on electricity and natural gas that minimise the profit risk in a spark spread contract. Before this decision is made, a manager will try to guarantee that spark spread contract payoffs ensure a

[1] Extracted from Risk.net glossary: a tolling agreement can be defined as a processing agreement for the conversion of an input product for a fee. In the electric power market, tolling agreements are typically between a power buyer and a power generator, under which the buyer supplies the fuel and receives an amount of power generated based on an assumed heat rate at an agreed cost. A tolling contract can contain contractual and operational constraints as, for example, start-up or shut-down charges, heat rate depending on the output level, minimum-run levels, a maximum number of restarts, etc. (see Deng and Xia (2005) and Woo et al. (2012)).

profitable activity for the company.[2] In fact, the spot price in the electricity market is determined by the intersection of the supply and demand curves at an auction in which the price for the 24 hours of the following day is settled. Power producers make their electricity offers according to their short-term marginal costs, principally fuel costs and CO_2–costs. Offers are then sorted from lowest to highest, obtaining the merit order curve, that is, the electricity offer curve. As power producers from renewable sources offer electricity at nearly zero marginal costs, they are the first to enter the merit order, followed by nuclear energy, coal or gas (depending on the country, coal before gas for UK and Germany and gas for the Netherlands) and fuel oil plants.[3] When electricity demand is low, the price setting units are coal power plants and in hours of high demand the price is set by gas units.

In the last few decades the demand for natural gas in Europe has consistently increased, reducing the use of coal and oil products in the space heating and industrial sectors. From the 1990s onwards, the proliferation of combined-cycle gas turbine (CCGT) plants in Europe has reinforced the importance of gas as an energy source, especially in power generation. Nevertheless, the demand for natural gas in Europe has stopped growing since 2008 because of several simultaneous factors: (i) stagnant power demand after the economic crisis of 2008; (ii) the rising share of renewables in the energy mix as part of the transition to a low carbon economy; (iii) the arrival of cheap coal after the US shale gas production boom in 2009 put gas-fired plants at a disadvantage in the merit order although in the last few years, it is usually coal before gas for the UK and Germany, and gas before coal for the Netherlands; and (iv) the fall of CO_2 allowance prices that exacerbated competition between natural gas and coal. Because of all these factors, gas-fired plants have been operating mostly in peak periods (except in the UK and Italy where gas plants still run on base load). The future of natural gas in the long-run European power generation mix will improve as it provides backup for the intermittency of renewables, and the effects of emissions legislation, and the

[2]The decision to run the plant may be made even if the spark spread is anticipated to be negative because the ramp-down (and subsequent ramp-up) costs are higher than the cost implied by a negative but lower spark spread value. Contractual and operational constraints if a tolling agreement is underwritten may also require the plant to sometimes run even when the spark spread is negative. Moreover, if the hedging strategy is considered, then hedging costs (bid-ask spread, for instance) may also affect the decision to run the plant or not. We thank one of the referees for this comment.

[3] See Sensfuß et al. (2008) and Cludius et al. (2014).

retirement of coal and nuclear capacity in the coming decades (see Honoré 2014, for more details). However, in the International Energy Outlook for 2016, an average increase of the 3.6% per year in natural gas consumption for power generation for the period 2020-2040 is projected for OECD Europe – this being the largest increase in the sector for any energy source (EIA, 2016).

Our empirical study has been applied to three European markets: the UK, the Netherlands, and Germany. These three markets have several important differences, especially notable because of the fuel mix in the power generation system and the shares of natural gas.[4] Electricity generation in Germany had the following fuel mix in 2014: 10% natural gas; 45% coal; 15% nuclear; 21% renewables; 7% biofuels; and 2% other fuels (see IEA, 2014). The sharp increase in renewable capacity in Germany has lowered electricity prices and gas-fired plants must face negative spark spread. Furthermore, backup for the intermittency of renewables is mostly provided by flexible lignite plants. This situation has prompted several gas-fired plants to apply for closure. Electricity generation in UK had the following fuel mix in 2015: 30% natural gas; 22% coal; 21% nuclear; 25% renewables; and 2% other fuels. Coal and gas-fired shares change each year, with some of the switching between the two reflecting fuel prices (see UK Government, 2016a). Gas power plants have a long-term role in the UK energy system by providing both flexibility and critical capacity, although utilisation is reducing over time (UK Government, 2016b). Electricity generation in the Netherlands had the following fuel mix in 2014: 50% natural gas; 31% coal; 4% nuclear; 10% renewables; and 5% other fuels (see IEA, 2014). The Dutch gas title transfer facility has grown enormously in the past years, and is now the biggest on mainland Europe. Recently, an induced earthquake caused by the extraction of natural gas from the Groningen field has forced the Dutch government to reduce extraction volumes (since 2014) to avoid more severe quakes. Nevertheless, Dutch market prices continue to be the most important reference across continental Europe.

[4] The observed energy mix in a country is the result of an interaction of fuel prices, available technologies, and energy policies. Atalla et al. (2017) analyses the evolution of the fossil fuel mix in the US, Germany and the UK. The US has experienced a relatively stable fossil fuel mix since 1980, while in Germany and the UK, the share of natural gas increased dramatically at the expense of coal. They found that fossil fuel prices dominated in determining the mix in the US, but that energy policy actions played an important role determining the transition from coal to natural gas in European countries

A common feature of natural gas and electricity prices is that spot price changes are partially predictable due to weather, demand, and storage level seasonalities.[5] Our paper is also innovative in uncovering and considering the seasonal effects detected in the spark spread that makes its changes partially predictable. Ederington and Salas (2008) showed that in these cases the linear regression hedging ratio estimate is inefficient, the riskiness of the spot position is overestimated, and the achievable risk reduction underestimated. We apply to the spark spread the methodology proposed by Ederington and Salas (2008) that overcomes these problems. In the Ederington and Salas (2008) framework the expected spot price changes are approximated using the information contained in the basis (futures price minus spot price). If futures prices are unbiased predictors of future spot price, the basis will be a measure of the expected change in the spot price until maturity (Fama and French, 1987).

The most insightful results obtained in the empirical experiment with the above three markets are: (i) the spark basis has an important predictive power explaining spot spark price changes (between 19.83% and 54.14% for the base load spark spread and between 3.67% and 44.43% for the peak load spark spread).; (ii) we analyse five possible futures hedging strategies and find that no hedging strategy clearly dominates the remaining strategies in all cases; (iii) results for Germany and the Netherlands are much better than results for the UK; (iv) the best performing monthly hedging strategies can produce risk reductions of between 20.05 and 48.90 for the spark spread; (v) individual monthly hedges of natural gas and electricity (base and peak load) produce higher risk reductions with values of between 31.22 and 69.06 per cent.

Hedging the spark spread contract payoffs with futures implies a simultaneous hedge on electricity and natural gas prices using futures contracts in both assets. The existing literature on hedging natural gas price risk with futures shows that risk reductions above 80% are possible for hedging periods equal or longer than a month (see Ederington and Salas (2008) and Martínez and Torró (2015)). Nevertheless, hedging electricity price risk using futures is more difficult because it is a

[5] See, for example, Koopman et al. (2007) and Martínez and Torró (2015) for electricity and natural gas prices, respectively.

non-storable commodity. The lack of a cash-and-carry arbitrage mechanism produces a looser relationship between spot and futures prices, especially as futures maturity becomes more distant. In addition, electricity spot price behaviour has some well-known characteristics: jumps, positive skewness, very high volatility, mean-reversion, seasonalities, and heteroscedasticity (see, for example, Koopman et al. (2007) for daily frequency data in European markets). Both effects combined produce a lower than usual correlation between spot and futures prices, and might generate a poor performance when hedging spot price risk with futures contracts.[6] Alexander et al. (2013) obtain a 70% of risk reduction when hedging the crack spread using NYMEX futures contracts on crude oil, gasoline and heating oil. Achieving such a high risk reduction seems much more difficult with the spark spread because it is much more unstable due to the lower correlation existing between natural gas and electricity compared to the correlations between oil, gasoline and heating oil.

We structure the remainder of this article as follows. In Section 2, we present the minimum variance framework. In Section 3, we describe our data and some preliminary descriptive statistics. In Section 4 we carry out an empirical exercise. We offer conclusions in Section 5.

2. The minimum variance hedge ratio

In the hedging literature (see Gagnon & Lypny, 1995; Kroner & Sultan, 1993; Myers, 1991) the optimal hedging ratio (OHR henceforth) is split in two parts. A initial speculative part depending on agent risk aversion and expected return on futures, and a pure hedging second part that is equal to the minimum variance hedge ratio (MVHR henceforth). Under the assumptions of either infinite risk aversion, or that futures prices follow a martingale, the OHR collapses to the MVHR. The OHR can be obtained using mean-variance utility functions – or any utility function supposing normality in the asset returns. Nevertheless, this result has a general validity as was demonstrated by Levi and

[6] For the California-Oregon-Border and Palo Verde futures traded at NYMEX Moulton (2005) obtains a risk reduction varying between -2% and 20% for daily hedges using monthly electricity futures. At the Nord Pool, Bystrom (2003) obtains risk reductions that range between 7% and 29% for weekly hedges. In Torró (2011), weekly spot price risk is hedged with weekly futures in the Nord Pool electricity market. It is shown that increasing the hedging period and closing futures positions near to its maturity may produce risk reductions over to 80%.

Markowitz (1979), who show that maximizing the mean-variance objective function provides a good approximation of maximizing expected utility regardless of the distribution of returns or the utility function chosen. Therefore, under the martingale assumption, i.e. that the expected return on futures is zero, the expected returns from a hedged portfolio will be unaffected by the number of futures contracts held, and therefore, the risk minimizing hedge becomes equivalent to the utility maximizing hedge.

Alexander et al. (2013) argue that the minimum variance (MV henceforth) framework has several advantages over optimal hedging (OH henceforth). OH is based on normality or mean-variance utility functions. These are unrealistic hypotheses. Furthermore, assuming futures prices are martingale, the high volatility in energy prices points to MV as the essential problem (see Alexander et al. 2013, page 699). Furthermore, Cotter and Hanly (2015) conclude that in the oil market the OH approach is not sufficiently different to warrant using a more complicated utility-based approach as compared with the simpler MV. Cotter and Hanly (2010) estimate the time-varying coefficient of relative risk aversion in energy markets by obtaining values between 0 and 1.25 (quite low values compared to financial markets). Cotter and Hanly (2010) assume that gasoline futures prices are not martingale and returns follow an AR(1). This is an interesting point if trying to separate optimal futures positions for long-hedgers and short-hedgers (Cotter and Hanly, 2010). Nevertheless, their results are disappointing because they obtain that MVHR outperforms OHR in all cases, using the expected utility as a measure of performance. Similarly, for the oil market and its refined products, Wang and Wu (2012) compare the effectiveness of several hedge ratio computation methodologies using the variance reduction and the utility obtained in a mean-variance utility function (using a degree of risk aversion of four). In both cases, the performance ranking of the hedge ratio computation methodologies is the same. Based on this evidence from the energy markets we use the MV framework. Below we describe the MV framework and the extension proposed in Ederington and Salas (2008).[7]

[7] For an excellent revision on futures hedging see Lien and Tse (2002).

Let's compute the payoffs of a spark spread contract, S_t, as:

$$S_t = S_t^e - aS_t^g$$

where S_t^e is the spot price of the electricity, S_t^g, the spot price of the natural gas, and a the conversion factor, considering the efficiency factor of a specific gas-fired plant and homogenising energy and monetary units. A long position in this contract can be seen as the summation of a long position in natural gas and short position in electricity – and will probably need to take short positions in natural gas futures/forward contracts and long positions in electricity futures/forward contracts to hedge the position in futures markets. The spark spread in the futures/forward markets is defined as:

$$F_t = F_t^e - aF_t^g$$

The spark spread in the futures/forwards markets can be explicitly traded as an individual contract or a specific position to take in each individual contract. In the most general case, let's suppose that this company is committed to a given position in the spot market and wishes to reduce its price risk exposure taking at the same time '*t*' positions in both forward/futures markets. The hedged company result per unit of spot at the end of the period, say, '*t*+1', is calculated as follows:

$$x_{t+1} = \Delta S_t - (\beta_t^e \Delta F_t^e - a\beta_t^g \Delta F_t^g) \tag{1}$$

where x_{t+1} is the value variation between t and t+1, $\Delta S_t = S_{t+1} - S_t$ is the spark spread value variation; $\Delta F_t^e = F_{t+1}^e - F_t^e$ and $\Delta F_t^g = F_{t+1}^g - F_t^g$ are the futures value variations for electricity and natural gas, respectively; and β_t^e and β_t^g are the corresponding hedging ratios. If β_t^e is positive (negative), short (long) positions are taken in electricity futures market. If β_t^g is positive (negative), long (short) positions are taken in natural gas futures markets. The hedger will choose β_t^e and β_t^g to minimise the risk associated with the random result x_{t+1}. We use realized returns instead log returns because we agree with the Alexander et al. (2013) methodology on several points. These authors argue that "...for assets with prices that can jump, log returns can be highly inaccurate proxies for percentage returns even when measured at the daily frequency. Additionally, since the hedged portfolio can have zero value, its percentage return may be even undefined. Thus, our hedging analysis is based on profit and loss (P&L) rather than on log or percentage returns".

A standard way to measure risk in economics is by the variance conditional on the available information, ψ_t. The risk of a hedge strategy is calculated as the variance of x_{t+1},

$$VAR[x_{t+1}|\psi_t] = VAR\left[\Delta S_t - (\beta_t^e \Delta F_t^e - a\beta_t^g \Delta F_t^g)|\psi_t\right] \tag{2}$$

A direct mathematical solution of this problem will lead us to minimize the function with respect to β_t^e and β_t^g. The measure of obtained risk reduction will finish the experiment. Nevertheless, we will contemplate various options to obtain β_t^e and β_t^g and we will compare the risk reduction obtained in each case and obtain optimal option.

To estimate these hedge ratios, a realistic methodology is to consider a conditional estimation using several econometric specifications modelling conditional second moments. The number of published papers modelling conditional covariance in energy markets has increased significantly in the last few years.[8] Estimated hedging ratios based on bivariate and tri-variate conditional covariance specifications obtained worse risk reductions to those hedging ratios estimated using simple linear regressions, therefore we decided to skip these results as the conclusions of the paper

[8] See Behmiri et al. (2016), Efimova and Serletis (2014), Chang et al. (2011), Ji and Fan (2011), Wang and Wu (2012) and Alexander et al. (2013)

will remain unchanged.[9] These results agree with Alexander et al. (2013), Martinez and Torró (2015), and Torró (2011) for energy markets.

Therefore, the methodology we propose to estimate the hedging ratios will be based on unconditional second moments based on the methodology proposed by Ederington (1979) and extended in Ederington and Salas (2008) to the case where spot price changes are partially predictable and futures prices are unbiased estimators of future spot prices. In this context, it is shown that the riskiness of the spot position is overestimated and the achievable risk reduction underestimated. Furthermore, as two commodities with respective futures contracts are considered there are several possibilities for estimating the hedging ratios in this framework. Specifically, the following cases are contemplated:

1. β_t^e and β_t^g are jointly obtained.
2. β_t^e and β_t^g are separately obtained in each market as independent problems.
3. $\beta_t^e = \beta_t^g = \beta_t$, jointly obtained but restricted to be equal.
4. $\beta_t^e = \beta_t^g = 1$, the naïve framework.
5. $\beta_t^e = \beta_t^g = 0$, the natural hedge.

Case 1. β_t^e and β_t^g are jointly obtained.

The hedge ratios that minimise the variance in equation (2) can be obtained by solving the first order conditions. When an unconditional probability distribution is used, the hedging ratios in

[9] The most widely used models are: (1) the VECH model proposed by Bollerslev et al. (1988); (2) the constant correlation model, CCORR, proposed by Bollerslev (1990); (3) the BEKK model of Engle and Kroner (1995) and (4) the dynamic conditional correlation or DCC of Engle (2002). Each model imposes different restrictions on the conditional covariance and can lead to substantially different conclusions in any application that involves forecasting conditional covariance matrices. Many studies introduce asymmetries in the second moments using the Glosten et al. (1993) approach. These specifications have also been used in multivariate variance modelling in energy prices. Chang et al. (2011) found that the diagonal version of the BEKK model beats the DCC model and other specifications in hedging effectiveness. Ji and Fan (2011) found that the DCC specification beats the remaining hedging alternatives. Wang and Wu (2012) obtain that simplified versions of the BEKK model (diagonal and scalar) had a better performance than the full BEKK, DCC, and CCORR. We have tested the above mentioned conditional variance models and many of its variants.

equation (2) can be estimated by ordinary least squares (OLS henceforth) from a linear relationship between spot and futures returns

$$\Delta S_t = \alpha - \beta^e \Delta F_t^e + a\beta^g \Delta F_t^g + e_t \tag{3}$$

This is the extension to the one future contract framework originally proposed in Ederington (1979). Correlation between natural gas and electricity may produce collinearity and hedge estimates with biased standard errors.

Here, we present the Ederington and Salas (2008) framework adapted to this case by reformulating equations (1) and (2) to introduce the partial predictability of the spark spread return. Under this new approach, the risk of the hedge strategy in equation (2) is reformulated as

$$VAR[x_{t+1}|\psi_t] = VAR\big[(\Delta S_t - E[\Delta S_t|\psi_t]) - (\beta_t^{e\prime} \Delta F_t^e - a\beta_t^{g\prime} \Delta F_t^g)|\psi_t\big] \tag{4}$$

Ederington and Salas (2008) propose using the basis (futures price minus spot price) at the beginning of the hedge as the information variable to approximate the expected spot price change. If futures prices are unbiased predictors of futures spot price, the basis will be a measure of the expected change in the spot price until maturity (Fama and French, 1987). An unconditional estimate of the hedge ratio in equation (4) can be obtained by estimating the following linear regression using OLS

$$\Delta S_t = \alpha - \beta^{e\prime} \Delta F_t^e + a\beta^{g\prime} \Delta F_t^g + \lambda(F_t - S_t) + e_t \tag{5}$$

where $\lambda(F_t - S_t)$ is used to estimate $E[\Delta S_{t+1}|\psi_t]$. Ederington and Salas (2008) show that OLS estimation of equation (5) produces an unbiased and more efficient estimation of the unconditional minimum variance hedge ratio than that obtained by using equation (3). This is true providing the expected change in the spot price is perfectly approximated with the product between the basis at the beginning of the hedge and its estimated coefficient (namely $\hat{\lambda}(F_t - S_t) = E[\Delta S_{t+1}|\psi_t]$).

Case 2. β_t^e and β_t^g are separately obtained.

It is interesting to investigate four more cases in which the above framework is simplified or restricted. A second possibility is to view the hedging problem as a double and independent hedging problem. That is, managing the two spot price risk separately, while measuring the hedging effectiveness jointly in the same performance measure. In this way, the unconditional hedging ratio estimation in the conventional framework will be obtained after separately estimating the following two linear regressions,

$$\Delta S_t^e = \alpha_1 + \beta^e \Delta F_t^e + e_{1,t}; \qquad \Delta S_t^g = \alpha_2 + a\beta^g \Delta F_t^g + e_{2,t} \tag{6}$$

and in the Ederington and Salas (2008) framework, we will use the following specification to obtain the unconditional hedging ratio estimation

$$\Delta S_t^e = \alpha_1 + \beta^e \Delta F_t^e + \lambda(F_t^e - S_t^e) + e_{1,t}; \quad \Delta S_t^g = \alpha_2 + a\beta^g \Delta F_t^g + \lambda(F_t^g - S_t^g) + e_{1,t} \tag{7}$$

Case 3. $\beta_t^e = \beta_t^g = \beta_t$, jointly obtained but restricted to be equal

A third option consists in reducing the dimensionality of the problem by using the same hedging ratio in both futures markets, or equivalently, trading on a futures/forward contract on the spark spread. That is, imposing the restriction $\beta^e = \beta^g = \beta$ in the unconditional estimation. This imposition will increase the estimation error. In this case, the conventional and the Ederington and Salas (2008) frameworks using unconditional estimation will be obtained, respectively, with the following expressions:

$$\Delta S_t = \alpha + \beta \Delta F_t + e_t \tag{8}$$

$$\Delta S_t = \alpha + \beta \Delta F_t + \lambda (F_t - S_t) + e_t \tag{9}$$

Case 4. $\beta_t^e = \beta_t^g = 1$*, the naïve framework.*

Hedging analysis is completed with the 'naïve' hedging ratios, that is, a hedge where futures positions have the same size but the opposite sign to the position held in the spot market. It is interesting to note that a perfect hedge is possible when futures positions are held until maturity and a naive hedge is adopted. Explicitly, if the maturity of the futures contracts matches with the final time of the hedge and $\beta_t^e = \beta_t^g = 1$, then the basis will be equal to zero in $t+1$, $F_{t+1} - S_{t+1} = 0$, with $S_t = S_t^e - aS_t^g$ and $F_t = F_t^e - aF_t^g$. In this very specific case, the variance of the result in Equation (2) will be zero. Naïve hedges in the Ederington and Salas (2008) approach will also eliminate the risk if in Equation (4) the expected changes in spot returns are substituted by $\lambda(F_t - S_t)$ and $\lambda = 1$, as the basis convergence on futures maturity requires. Nevertheless, when futures positions are closed before maturity, the naïve framework may perform poorly. Following the results of Torró (2011) for electricity and Martínez and Torró (2015) for natural gas, the naive strategy can produce a good performance, and even represent the best hedging strategy in some cases (for long period hedges especially when futures positions are closed near to the futures maturity). That is, when the premises of this approach are close to being true.

Case 5. $\beta_t^e = \beta_t^g = 0$*, the natural hedge*

If the electricity market is not very competitive and there is no a diversified energy source generation mix, it is possible that main fuel price shocks would be transferred to the electricity prices. That is, the unhedged position may be optimal in some energy markets in which natural gas has a significant share in the power source energy mix, and there is no fully competitive behaviour by electricity producers and marketers. This is known as the natural hedge ($\beta_t^e = \beta_t^g = \beta^e = \beta^g =$

0). When electricity and natural gas prices are highly and positively correlated, gas-fired plants are said to enjoy a 'natural hedge'. Guo et al. (2016) found that a typical gas-fired power plant enjoyed a natural hedge in the UK in the period 2006 to 2011 using its daily aggregated dispatch decisions. That is, it was better off facing uncertain spot prices rather than locking in its generating costs. However, these authors argue that the natural hedge is not a perfect hedge, i.e., even modest risk aversion makes using some further hedging strategy optimal.

Measuring hedging effectiveness

In the empirical application in Section 4, the effectiveness of the hedging strategies are compared. The hedging ratios obtained following the conventional framework are labelled 'without basis' – and those hedging ratios estimated by following the Ederington and Salas (2008) framework are labelled 'with basis'. The hedging effectiveness of each strategy is obtained by using Equations (2) and (4) to compute the risk in each framework and then comparisons are made with respect to the spot position: that is $VAR[\Delta S_t|\psi_t]$ and $VAR[\Delta S_t - E[\Delta S_t|\psi_t]|\psi_t]$, respectively. Furthermore, *ex post* and *ex-ante* results are distinguished by splitting the data sample into two parts. In the first part, the hedging strategies are compared *ex post*, whereas in the second part, an *ex-ante* approach is used. That is, in the *ex-ante* study, strategies are compared using forecasted hedge ratios, and models are estimated when a new observation is considered.[10]

To test if the difference in hedging reductions are statistically significant we performed White's reality check as described in Lee and Yoder (2007) – but using equation (4) as a risk measure instead equation (2) because we were applying the Ederington and Salas (2008) approach. For technical details, we referred to Lee and Yoder (2007a), Lee and Yoder (2007b), and White (2000). Specifically, the variance of the estimated optimal hedged portfolio in the *ex-ante* study under the Ederington and Salas (2008) approach was computed as:

[10] In the Ederington and Salas (2008) framework, the λ coefficient in equations (5), (7) and (9) is estimated each time a new observation is introduced in the *ex-ante* study. To enable a comparison between the obtained risk reductions across the five studied cases, we have measured the unexpected shocks in the spot position using the λ value estimated from equation (9). The results are almost identical when equation (4) is used instead.

$$VAR\left[(\Delta S_t - \hat{\lambda}_t(F_t - S_t)) - (\hat{\beta}_t^{e\prime}\Delta F_t^e - a\hat{\beta}_t^{g\prime}\Delta F_t^g)\right] \tag{10}$$

where $\hat{\lambda}_t$, $\hat{\beta}_t^{e\prime}$ and $\hat{\beta}_t^{g\prime}$ are predicted parameter estimations conditioned for the information available on *t* as previously described. For each pair of hedging strategies, and for each observation included in the *out of sample* period, the following performance measure is computed:

$$\hat{f}_{k,t+1} = -\left[\left(\Delta S_t - \hat{\lambda}_t(F_t - S_t)\right) - \left(\hat{\beta}_{k,t}^{e\prime}\Delta F_t^e - a\hat{\beta}_{k,t}^{g\prime}\Delta F_t^g\right)\right]^2$$
$$+\left[\left(\Delta S_t - \hat{\lambda}_t(F_t - S_t)\right) - \left(\hat{\beta}_{BM,t}^{e\prime}\Delta F_t^e - a\hat{\beta}_{BM,t}^{g\prime}\Delta F_t^g\right)\right]^2 \tag{11}$$

where $\hat{\beta}_{BM,t}^{e\prime}$ and $\hat{\beta}_{BM,t}^{g\prime}$ are the hedging ratios estimate of the strategy used as a benchmark; that is, the hedging strategy with the lowest risk reduction in each pair of strategies compared. And each pair $\hat{\beta}_{k,t}^{e\prime}$ and $\hat{\beta}_{k,t}^{g\prime}\,\hat{b}_{k,t}^{\prime}$ correspond to the k hedging strategy belonging to the set of all possible hedging strategies with better risk reductions than the compared benchmark strategy. White's reality check is based on the following performance statistic:

$$\bar{f} = \frac{1}{n}\sum_{t=R}^{T}\bar{f}_{t+1} \tag{12}$$

where *n* is the number of observations in the *out of sample* experiment, that is $n = T - R$. The null hypothesis that the best performing hedging strategy from each pair of possible strategies considered has no predictive superiority over the worst performing in each pair is given by:

$$H_0\colon E[f_k^*] \leq 0 \tag{13}$$

where f_k^* is the true performance value for each model applied to the data. Following White (2000), White's reality check is implemented with the stationary bootstrap resampling method of Politis and Romano (1994) in which pseudo-time series are generated by resampling blocks of random length drawn from a geometric distribution. This procedure is repeated to generate an approximate sampling distribution of the $\bar{f}$ performance measure. To apply the stationary bootstrap method of Politis and Romano (1994), the smoothing parameter q and the resamplings are set to 0.5 and 10000, respectively.

3. Data and preliminary analysis

We examine three representative European markets: the United Kingdom, the Netherlands, and Germany. Table 1 summarises data sources used for the three markets. For both electricity and gas, we use futures prices (except for UK electricity where we employ forward prices because of the lack of liquidity in futures negotiation in this market). The electricity market demand pattern depends on the time of the day. Hours in which demand is high and capacity is tight are known as *peak load* hours. Contracts supplying electricity 24 hours a day are known as *base load*. We analyse short time hedges of weekly and monthly frequency with the monthly front futures contract for the UK and the Netherlands, and with weekly and monthly front electricity futures for Germany. Weekly futures time series are built by taking the closing prices on Wednesday (or the day before if non-tradable) and monthly futures time series are constructed by picking the last negotiated Wednesday of the month (to avoid the instabilities of the last trading day we take the previous day if the last Wednesday is the last trading day of the month) for both electricity and natural gas futures. The spot electricity price is the weekly/monthly average of the daily spot prices for weekly/monthly frequency hedges and the spot natural gas price is the closing spot/day ahead price for the day considered.

In the UK electricity market, the daily spot price is calculated as the average price of the volume-weighted reference price for each half hour settlement period, from 07:00 until 19:00 Monday to

Friday if peak hours and from 23:00 until 23:00 of the next day for every single day of the week if base hours. The base and peak forward prices are a composite of Reuters broker contributors. Regarding natural gas prices we use the *system average price* (SAP)[11] provided by the National Grid as spot price, and the UK Natural Gas Futures contracts negotiated at Intercontinental Exchange (ICE) as futures price.

The electricity data for the Netherlands is from APX (spot prices) and Reuters (futures prices). We use the day ahead APX Index as the daily electricity spot price. The base load daily spot price is the average of the hourly prices of all hours of the day; and the peak load daily spot price is the average of hourly prices from 8:00 until 20:00. The electricity futures are negotiated in ICE ENDEX. The natural gas spot price for the Netherlands is the TTF day ahead price from Platts; and the TTF futures price is the front month contract from ICE.

The electricity data for Germany is from European Energy Exchange (EEX). We use the Phelix Day Base and Phelix Day Peak Indexes as spot references. The index is calculated as the mean value of the hourly prices traded from 00:00 until 24:00 for all days of the week if Phelix Day Base Index; and from 08:00 until 20:00, Monday through Friday for the Phelix Day Peak Index. For futures prices, we take the Phelix month and week futures (available also for base and peak load). The natural gas market used as a benchmark for Germany is the TTF because although Germany has its own natural gas hubs, they are insufficiently liquid to be significant.

The spark spread is computed as electricity prices minus natural gas corrected with some technical adjustments. Following Borovkova (2004) and Borovkova and Geman (2006) the spark spread in the UK (£/MWh) can be computed as the difference between the electricity price (£/MWh) and 0.68 times natural gas futures price (pence/therm).[12] In the Dutch and German markets, the natural gas

---

[11] It is the average price of all gas traded via the on-the-day commodity market mechanism for the gas day.

[12] The factor 0.68 is obtained by transforming therms to MWh dividing by 0.0293071 (MWh per therm), then dividing by 0.5 (assumed generator efficiency ratio) and transforming pence to pounds by dividing by 100. The full number is 0.6824284. Note that with a contract unit in the NBP natural gas futures represents 1000 therms per day or its equivalent 29,3071 MW per day. For each MWh sold in the electricity market, it is necessary to burn $(1/e)\times(1/0.0293071)$ therms of gas – that is 68.24285 therms using $e = 0.5$ as efficiency ratio. For base load 24 hour electricity contracts it is necessary to burn 25,000 therms to obtain 15 MW each hour if an efficiency ratio of 0.4913 is used $(25{,}000/(24\times(1/e)\times(1/0.0293071)) = 15.031)$. This calculation enables trading the spark spread for contracts

price is measured in €/MWh. The underlying asset in the futures contracts correspond to 1 MWh for each hour contained in the delivery period of the contract. In these markets the spark spread is obtained as the electricity price minus two times the natural gas price, supposing an efficiency ratio of 0.5. The efficiency ratio measures how many units of electricity are produced with 1 unit of natural gas in a gas-fired plant. When clean spark spread is computed, the spark spread is reduced with the CO_2 allowance price corrected with a gas emissions intensity factor. In the three markets, we use the value of 0.38 for the gas emissions intensity factor.[13] Additionally, for the case of the UK, the EU emissions allowance prices are transformed from euros to pounds using the exchange rate obtained from the Bank of England. Furthermore, in the UK the carbon price support is added to the EU emissions allowance price expressed in pounds sterling to obtain the clean spark spread.[14] Figure 1 shows that benchmark values of the spark spreads have become negative in many cases after 2009 because rising renewables, reduced coal and CO_2 prices, and low power demand forced down electricity prices and left little room for gas-fired generation in Europe. In this context, it is important to optimise the hedging performance not to incur losses. For a specific power gas-fired plant, the most important factor determining the sign of the spark spread is its particular heat rate. In fact, the heat rate varies significantly across the range of generation stock, and even for a single plant it can depend heavily on the temperature and on the way the plant is being utilized (being much higher if it is frequently ramping up and down). Charalampous and Madlener (2015) state that natural gas-fired plants are suffering from severe losses since wholesale peak-load electricity prices have plummeted while renewable electricity generation has surged, making hedging in today's energy markets essential for power plant operators (given that many energy companies experience large problems in maintaining profitability).

---

containing the same underlying period by taking three positions in electricity contracts for each pack of five natural gas contracts. In the UK, this computation is the way in which agents trade the spark spread in the market. For peak load electricity contracts, the number of contracts must be taken in the proportion of peak hours contained in the whole delivery period – but the spark spread computation procedure will not change.

[13] In Abadie and Chamorro (2008) the efficiency ratio for CCGT plants is approximated with values ranging between 50% and 60%. Capitán and Rodríguez (2013) use an efficiency ratio 0.55 and a gas emissions intensity factor of 0.37. We use the same values as Reuters for the efficiency ratio (0.5) and the gas emissions intensity factor (0.38).

[14] The Carbon Price Support (CPS) is a tax that businesses using fossil fuels to generate electricity must pay on those fuels. The cost of the British Government CPS levy in GBP per mega tone of CO_2 is 9.55 from 1 April 2014 to 31 March 2015, 18.08 from 1 April 2015 to 31 March 2016 and 18.00 from 1 April 2016 to 31 March 2017.

Is common in the literature to read that when a futures contracts hedge is taken, the spot price risk is exchanged for the basis risk.[15] In Table 2, the basis risk of each commodity is reported. The most important comment on this table comes when volatilities of the bases of the spark spread and clean spark spread are compared. Both variables have almost the same basis risk since up to the second decimal place, volatility values are equal. This is because the introduction of CO_2 prices has no effect on the spark spread bases because CO_2 futures and spot prices are virtually indistinguishable variables. We also observe in Table 3 that correlation between CO_2 spot and futures returns is 0.99 as in Trück and Weron (2016), and that both variables have almost the same statistical properties. From Tables 2 and 3, it can be concluded that the spark basis and the clean spark basis have virtually the same risk properties. Therefore, the dimensionality of the problem of hedging risk under the minimum variance framework for the clean spark spread can be reduced to hedging the risk of the spark spread. Nevertheless, it must be said that in the minimum variance framework, the return of a hedged strategy is not considered. Consequently, before engaging in a hedging risk strategy, the electricity producer must decide if burning fuel in a natural gas power plant is profitable or not. This decision depends on the level of the clean spark spread and technological and contractual constraints. If the payoffs are going to be positive, the plant manager will need to buy CO_2 futures or spot contracts to ensure the profitability of turning on the plant. A subsequent decision is to reduce the spark spread risk for a specific period by taking positions in the electricity and natural gas futures markets.

Summary statistics for electricity, natural gas, and sparks spreads are reported in Table 4. One common result of all the return time series is the positive excess kurtosis. The skewness sign varies across time series and markets, consequently, no conclusive feature is observed. It is interesting to note that electricity and the spark returns have a similar volatility. This result may imply that the main source of uncertainty in the spark spread seems to come from electricity price spikes. Finally,

[15] The result of a simple naïve hedge can be seen as the subtraction of futures returns to spot returns, $(S_{t+1} - S_t) - (F_{t+1} - F_t)$, or equivalently, as the basis return, $(F_{t+1} - S_{t+1}) - (F_t - S_t) = \Delta Basis_t$. The uncertainty of the hedge result then depends on the uncertainty of the basis at the end of the hedge. That is, the basis risk. See Hull (1997) pages 32 to 35.

from the comparison between each pair of spot and futures return volatility, it can be observed that in 28 out of 30 cases, spot return volatility is larger than futures return volatility.

Correlations are reported in Tables 5. The highest values of the correlation between spot and futures pairs correspond to natural gas, with correlation values ranging between 0.55 and 0.62. For electricity and spark spreads spot-futures pairs, we have lower values: between 0.10 and 0.30 for weekly frequency and between 0.26 and 0.55 for monthly frequency. It is then crucial for hedging purposes to increase the hedging period, especially for electricity and spark spread risk management. Another interesting result comes when correlations between futures returns of natural gas and electricity base load are observed. In monthly frequency (Panels E, F, and G) this correlation has values of between 0.57 and 0.78; and in weekly frequency (Panels A, B, and C) it takes values between 0.42 and 0.50. Consequently, these commodities are closely related. This fact is especially clear for monthly returns in the UK as the natural gas returns and all the electricity returns have correlation values between 0.50 and 0.69. Therefore, natural gas prices have an important pricing role in the electricity market. This is an expected result, as natural gas is the most import fuel source of the generation mix in the UK electricity market. As expected, the correlation between natural gas return and the spark spread return is negative in most cases and not significant in many cases. Finally, for electricity and spark spread, the correlation between base and peak load returns is very high, especially for the pair of futures and for the pair of spot returns, with values of about 0.90 in most cases. Nevertheless, each of these futures contracts with its underlying asset has a lower correlation. For example, for monthly returns, electricity futures and the underlying assets have correlations ranging between 0.39 and 0.50, with the highest values corresponding to base load pairs. The spark spreads futures-spot correlation is lower with values ranging between 0.26 and 0.37. Taking this information into account, one would expect that a successful hedge in the spark spread will be much more difficult than hedging risk with futures separately in the electricity or natural gas markets.

Weekly returns cross-lagged correlations are displayed in Table 6. In the previous paragraph, we have seen that simultaneous correlation between natural gas returns and electricity returns are high in many cases, particularly in the case of natural gas futures and base load futures. Now in Table 6, we want to examine the dynamics of this relationship computing one-week cross-lagged correlation coefficients. The highest and most significant values correspond to the first and second rows of this table. That is, an increase (decrease) in natural gas price will probably be followed by an increase (decrease) in electricity prices. The wholesale gas price and the wholesale electricity price broadly move together, as for much of the year gas-fired generation is the marginal plant and therefore sets the wholesale electricity price (UK Government, 2012). The high values of simultaneous and cross-lagged correlation between electricity and natural gas returns point to a significant degree of price shock transfer from natural gas to electricity. As we have discussed in the previous section, in the case of a perfect price shock transfer between both commodities, gas-fired plants producing electricity would enjoy a natural hedge and not need to take positions in futures markets.

4. Results

Ederington and Salas (2008) demonstrated that when spot price returns are partially predictable, the standard method of estimating hedging ratios based on Ederington (1979) is inefficient and the risk reduction obtained with the hedge is underestimated. To overcome these problems, Ederington and Salas (2008) propose approximating the expected spot return using the lagged value of the basis (see Section 2). Before applying this methodology, it is necessary to measure the predictive power of the basis on returns, particularly in the spot case. Results are reported in Table 7. For the Netherlands and Germany, lagged values of the basis explain between 17 and 60 per cent of subsequent spot returns and they have a much lower explicative power for futures returns. Moreover, the determination coefficients are higher in spot returns than in forward returns in all cases. This result agrees with Borovkova and Geman (2006) and Lucia and Schwartz (2002) when they state that seasonal patterns in spot prices and the forward curve should be significantly different.

As in most energy commodities, a seasonal feature is expected for the spark spread (see Borovkova and Geman (2006)). It is important to highlight that with the exception of the peak spark spread return for the UK, in the remaining cases, spark returns can be explained by the lagged values of their bases with determination coefficients ranging between 16.18 and 54.14 per cent. If the objective of the risk manager is to reduce the uncertainty of unexpected changes in the spark spread using futures, the expected changes must be separated from the total changes in the spark spread risk measure. This result is new in the literature and is very relevant for the design and performance measure of hedging strategies using futures contracts. The reason for the existence of these forecastable pattern in the spark spread comes from the existence of seasonal patterns in energy commodity demand due to climate oscillation throughout the year. Previous results in Torró (2011) and Martinez and Torró (2015) confirm the existence of this feature in European electricity and natural gas markets, but this is the first time it is found in spark spreads.

Tables 8 and 9 show the hedging effectiveness analysis of the strategies presented in Section 2. The five assets considered are the spark spread for the base and peak load in Table 8 and electricity for the base and peak load, and natural gas in Table 9. In each of the above cases, weekly and monthly data frequency results are reported. We considered electricity and natural gas separately because it is important information and it is not obvious that a successful separated hedging strategy for electricity and natural gas will produce a successful hedge of the spark spread.

We first discuss results corresponding to the spark spreads. Figure 2 reports the hedging ratios estimated as described in Section 2 for the spark spreads for a monthly frequency. The sample period is divided into *ex post* and *ex-ante* sub-periods when the number of observations is sufficiently large. A vertical line separates both periods in panels d), e) and f). With the exception of the natural gas hedging ratio in Figure 2-a (when it is jointly estimated), all the hedging ratios are positive. It is also interesting to note hedging ratios in electricity futures when estimated jointly (case 1) or restricted (case 3), as both hedge ratios are almost equal in all the cases. This fact indicates that the optimal least squares method prioritises the electricity hedging ratio to minimise estimation errors because of electricity jumps. Looking at the best performing strategies marked with an asterisk in Table 8, we cannot point out a hedging strategy that dominates the risk reduction achieved. The best performing hedging strategy changes across markets, periods, and data frequency. Moreover, risk reduction attained corresponding to the conventional framework is clearly underestimated. In tables 8 and 9, under the Ederington and Salas (2008) framework, risk reduction really attained improvements of between 1% and 18% in weekly hedges and between 7% and 27% in the monthly hedges. The worst results for the spark spread risk reduction correspond to the UK. In the case of the peak load spark spread at weekly frequency appearing in Panel C in Table 8, it can be observed that in the out-of-sample period no hedging strategy produces a risk reduction. In this case, it is best to leave the spot position unhedged. Monthly hedges for the UK case significantly improve the attained risk reduction. In this case, the optimal hedging strategies obtain a risk reduction of 20.05 and 25.05 per cent for the base and peak load spark spreads, respectively. Results for the Netherlands and Germany are much better. The risk reduction reached for optimal weekly hedges varies between 16.38 and 34.75 per cent. In monthly hedges in these two countries, the risk reduction can attain values ranging between 28.92 and 48.90 per cent. To sum up, the main result for the spark spread are: (i) monthly hedges obtain a better hedging performance than weekly hedges; (ii) there is no clear hedging strategy that clearly dominates the remaining strategies; (iii) results for Germany and the Netherlands are much better than the results for the UK; (iv) the best performing monthly hedging strategies can attain risk reductions ranging between 20.05 and 48.90.

To better understand spark spread hedging results we have extended the hedging analysis to individual hedges of electricity (peak and base load) and natural gas prices. Results for electricity are similar to spark spread results. Weekly hedges for electricity produce poor results, and in one case even increase the risk after hedging (see Panel C in Table 9). Nevertheless, excellent results are obtained in monthly hedges, especially in the base load case. In this case, the risk reduction produces values ranging between 48.69 and 60.35 per cent. For the peak load case, these values range between 31.22 and 55.89. Electricity hedges must then be made for long periods, otherwise the result can be the opposite of what was expected.

Finally, hedging results for weekly and monthly periods of the natural gas price are also reported in Table 9. Risk reduction for weekly and monthly periods are above 41.19 and 56.44 per cent, respectively. Therefore, compared with spark spread and electricity, natural gas price risk is the easiest to hedge. We also compute hedging effectiveness with another risk measures especially suitable for examining how optimal variance hedging strategies are dealing with spikes in spot prices, such as the value at risk (VaR) and the expected shortfall (ES). VaR(α) is the cut-off point where the probability that a larger loss in the hedged portfolio will not happen with a probability greater than α percent. The VaR at confidence level α is the quantile of the loss distribution. Expected Shortfall (ES), also known as conditional VaR (CVaR), measures the expected value of the losses when cut-off points of VaR are exceeded and is computed as the mean value of those hedging portfolio results contained in the tail. It is a useful measure for hedgers because it provides an estimation of the magnitude of a possible loss along with the probability of loss occurrence. We calculate VaR and ES for week and month hedges with the 5% confidence level using historical simulation approach based on the empirical distribution. The results, in Table 10 to 15, show that spikes are greatly reduced when spot positions are hedged and when hedge duration increases. These reductions have a similar pattern to the hedging effectiveness of variance reported in Tables 8 and 9.

Finally, the White's test described in Section 2 was applied to test the statistical significance of variance risk reduction differences attained for the out-of-sample periods for each pair of hedging strategies. In all cases, the null hypothesis of no improvement in the risk reduction is rejected at 5% of significance level. Consequently, we can conclude that hedging performance differences are statistically significant in all cases.

5. Conclusions and policy implications

There is an extensive literature on valuing and hedging power plants using the real option approach. The same can be said for price risk management using futures contracts. Nevertheless, this paper is the first (to our knowledge) to discuss spark spread risk management with futures contracts. We have focussed on three European markets in which the natural gas share in the fuel mix for generating electricity varies considerably: Germany (10%); the United Kingdom (30%); and the Netherlands (50%). Consequently, we feel our results should be of interest for all agents in those countries and energy markets in which natural gas is part of the fuel mix for power generation.

An important preliminary result is obtained when the spark spread risk and the clean spark spread risk are compared. It is found that both variables are indistinguishable and the dimensionality of the problem can be reduced by considering only electricity and natural gas prices. This is because CO_2 spot and futures prices are almost perfectly correlated and the basis risk of a hedge is the same for both spreads. Further to the spark spread sign, gas-fired plants managers would consider running the plant if the spark spread contract payoffs ensures a profitable activity for the company considering all the contractual and operational clauses, the technological characteristics of the plant, and costs of the financial hedging strategy.

One generally accepted feature of energy prices is the presence of seasonal behaviour. We find that spark spread returns can be partially anticipated and the Ederington and Salas (2008) framework should be applied. The application of the Ederington and Salas (2008) approach highlights that risk reduction is underestimated in the standard approach (Ederington, 1979) due to the existence of a seasonal pattern that can be subtracted from the total returns.

Results in this paper show that an individualised risk management of electricity and natural gas prices is not always the best solution. Hedging the spark spread with futures is more difficult than hedging electricity and natural gas price risks with their respective futures contracts.[16] Whereas spark spread risk reduction for monthly periods attains values ranging between 20.05 and 48.90 per

[16] Liu et al. (2017) obtain the same conclusion for the crack spread and its individual constituents.

cent, electricity price risk attains reductions ranging between 48.69 and 69.06 per cent for base load prices and between 31.22 and 55.89 per cent for peak load prices. Optimal strategies for natural gas prices for monthly periods produce risk reductions ranging between 56.54 and 61.77 per cent.

We feel our results should be of interest for electricity producers as the evolution of the spark spread is towards narrow values and, in many cases, gas-fired power plants are being mothballed while awaiting more profitable scenarios. Reducing the activity risks of these agents is an important issue. The paper is important for regulators because gas-fired power plants can back up energy from renewable energy sources because of their flexibility and reduced emission of polluting gases (compared to other fuels). And the paper is also of interest to academic audiences because of the innovative results in the scientific literature.

References

Abadie, L. M., and Chamorro, J. M. (2008) Valuing flexibility: The case of an integrated gasification combined cycle power plant. Energy Economics 30, 1850-1881.

Alexander C., Prokopczuk M., and Sumawong A. (2013) The (de)merits of minimum-variance hedging: Application to crack spread. Energy Economics 36, 698-707.

Atalla, T., Blazquez, J., Hunt, L. C., and Manzano, B. (2017) Prices versus policy: An analysis of the drivers of the primary fossil fuel mix. Energy Policy 106, 536-546.

Behmiri, N. B., Manera, M., and Nicolini, M. (2016) Understanding dynamic conditional correlations between commodities futures markets. Fondazione Eni Enrico Mattei, Nota di Lavoro 17.

Boie, I., Fernandes, C., Frías, P., and Klobasa, M. (2014) Efficient strategies for the integration of renewable energy into future energy infrastructures in Europe — An analysis based on transnational modelling and case studies in nine European regions. Energy Policy 67, 170-185.

Bollerslev, T. (1990). Modeling the coherence in short-run nominal rates: a multivariate generalized ARCH approach. Review of Economics and Statistics, 72, 498-505.

Bollerslev, T., Engle R. F., and Wooldrige, J. M. (1988). A capital asset pricing model with time varying covariances. Journal of Political Economy, 96, 116-31.

Borovkova, S. (2004). The forward curve dynamic and market transition forecast. Chapter 13 in Bunn D. W. (editor), Modelling prices in competitive electricity markets. John Wiley and Sons Ltd. Chichester, Sussex, UK.

Borovkova, S., and Geman, H. (2006) Analysis and modelling of electricity futures prices. Studies in Nonlinear Dynamics & Econometrics 10(3), article 6, 1-14.

Bystrom, H. N. (2003). The hedging performance of electricity futures on the Nordic power exchange. Applied Economics 35, 1-11.

Capitán Herráiz, Á., and Rodriguez Monroy, C. (2013) Analysis of the Iberian power forward price formation. IEEE Transactions on Power Systems 28(3), 2942-2949.

Chang, C.-L., McAleer, M., and Tansuchat, R. (2011) Crude oil hedging strategies using dynamic multivariate GARCH. Energy Economics 33, 912-923.

Charalampous, G., and Madlener, R. (2016) Risk management and portfolio optimizacion for gas- and coal-fired power plants in Germany: A multivariate GARCH approach. Journal of Energy Markets 9(2), 69-94.

Cheung, Y.-W., and Ng, L. K. (1996) A causality-in-variance test and its application to financial market prices. Journal of Econometrics 72, 33-48.

Cludius, J., Hermann, H., Matthes, F. C., and Graichen, V. (2014) The merit order effect of wind and photovoltaic electricity generation in Germany 2008–2016: estimation and distributional implications. Energy Economics 44 , 302–313.

Cotter, J., and Hanly J. (2010) Time-varying risk aversion: an application to energy hedging. Energy Economics 32, 432-441.

Cotter, J., and Hanly, J. (2015) Performance of utility based hedges. Energy Economics 49, 718-726.

Deng, S.-J., and Xia, Z. (2005). Pricing and Hedging Electricity Supply Contracts: a Case with Tolling Agreements. Manuscript, Georgia Institute of Technology.

Ederington, L. H. (1979) The hedging performance of the new futures markets. The Journal of Finance 34, 157-170.

Ederington, L. H., and Salas, J. M. (2008) Minimum variance hedging when spot price changes are partially predictable. Journal of Banking and Finance 32, 654-663.

Efimova O., and Serletis, A. (2014) Energy markets volatility modelling using GARCH. Energy Economics 43, 264-273.

EIA (2016). International Energy Outlook 2016. US Energy Information Administration.

Emery, G. W., and Liu, Q. (W.) (2002) An analysis of the relationship between electricity and natural-gas futures prices. The Journal of Futures Markets 22, 95-122.

Engle, R. (2002). Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics 20, 339-350.

Engle, R. F., and Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. Econometric Theory, 11, 122-50.

Fama, E. F., and French, K. R. (1987). Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage. Journal of Business 60, 55-74.

Gagnon, L. and G. Lypny (1995) : "Hedging Short-Term Interest Risk under Time-Varying Distributions", The Journal of Futures Markets, 15, 767-783.

Glosten, L. R., Jagannathan, R., and Runkel, D. E. (1993). On the relation between the expected value and volatility of nominal excess return on stocks. The Journal of Finance, 48, 1779-801.

Guo, X., Beskos A., and Siddiqui, A. (2016) The natural hedge of a gas-fired power plant. Computational Management Science 13, 63-86.

Honoré, Anouk (2014). The outlook for natural gas Demand in Europe. The Oxford Institute for Energy Studies, paper NG87.

Hull, J. C. (1997) Options, futures, and other derivatives. Third Edition. Prentice Hall, New Jersey.

International Energy Agency (2014). Statistics at the website: www.iea.org.

Ji, Q., and Fan, Y. (2011) A dynamic hedging approach for refineries in multiproduct oil markets. Energy 36, 881-887.

Koopman, S. J., Ooms, M., and Carnero M. A. (2007). Periodic seasonal Reg-ARFIMA-GARCH models for daily electricity spot prices. Journal of the American Statistical Association 102, 16-27.

Kroner, K. F., and J. Sultan (1993): "Time-Varying Distributions and Dynamic Hedging with Foreign Currency Futures", Journal of Financial and Quantitative Analysis, 28, 535-51.

Lee, H. T., and Yoder, J. K. (2007a). Optimal hedging with a regime-switching time variance correlation GARCH model. The Journal of Futures Markets, 27, 495-516.

Lee, H. T., and Yoder, J. K. (2007b). A bivariate Markov regime switching GARCH approach to estimate time varying minimum variance hedge ratio. Applied Economics, 39, 1253-65.

Levy, H., and Markowitz, H. (1979) Approximating expected utility by a function of mean and variance. American Economic Review 69, 308-317.

Lien, D., and Tse, Y. K. (2002). Some recent developments in futures hedging. Journal of Economic Surveys 16, 357-96.

Liu, P., Vedenov, D., and Power G.J. (2017). Is hedging the crack spread no longer all it's cracked up to be? Energy Economics 63, 31-40.

Lucia, J.J., and E.S. Schwartz (2002). Electricity prices and power derivatives: Evidence from the Nordic Power Exchange. Review of Derivatives Research, 5, 5-50.

Martínez, B., and Torró, H. (2015) European natural gas seasonal effects on futures hedging. Energy Economics 50, 154-168.

Martínez, B., and Torró, H. (2017) Hedging spark spread risk with futures. Instituto Valenciano de Investigaciones Económicas, Working paper, WP-EC-2017-01.

Moulton, J. S. (2005). California electricity futures: The NYMEX experience. Energy Economics 27, 181-94.

Myers, R. J. (1991) : "Estimating Time-Varying Optimal Hedge Ratios on Futures Markets", The Journal of Futures Markets, 11, 39-53.

Peters, J. C. (2017) Natural gas and spillover from the US Clean Power Plan into the Paris Agreement. Energy Policy 106, 41-47.

Pless, J., Arent, D. J., Logan, J., Cochran, J., & Zinaman, O. (2016). Quantifying the value of investing in distributed natural gas and renewable electricity systems as complements: Applications of discounted cash flow and real options analysis with stochastic inputs. Energy Policy, 97, 378-390.

Politis, D., and Romano, J. P. (1994). The stationary bootstrap. Journal of the American Statistical Association, 89, 1303-13.

Sensfuß F., Ragwitz M., and Genoese, M. (2008). The merit-order effect: a detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy Policy 36, 3076–308

Torró, H. (2011). Assessing the Influence of Spot Price Predictability in Electricity Futures Hedging. Journal of Risk 13(4), 31-61.

Trück S., and Weron, R. (2016) Convenience yields and risk premiums in the EU-ETS – Evidence from the Kyoto commitment period. The Journal of Futures Market 36, 587-611.

UK Government (2012). A call for evidence on the role of gas in the electricity market. Department of Energy and Climate Change. May.

UK Government (2016a). Quarterly Bulletin on Energy Trends. Department of Energy and Climate Change. November.

UK Government (2016b). A call for evidence for a smart, flexible energy system. Department of Business, Energy and Industrial Strategy. November.

Wang, Y., and Wu, C. (2012) Forecasting energy market volatility using GARCH models: Can multivariate models beat univariate models? Energy Economics 34, 2167-2181.

White, H., 2000. A reality check for data snooping. Econometrica 68, 1097-1126.

Woo, C.-K, Horowitz, I., Horii, B., Orans, R., and Zarnikau, J. (2012) Blowing in the wind: vanishing payoffs of a tolling agreement for natural-gas-fired generation of electricity in Texas. The Energy Journal 33, 207-229.

Annex I: Tables

Table 1. Data description

Market	Variable	Unit	Source (Spot/Futures)	Period
UK	Electricity base load	GBP/MWh	Reuters/APX	November 2007-February 2016
	Electricity peak load	GBP/MWh	Reuters/APX	November 2004-February 2016
	Gas	pence/therm	Platts/Intercontinental Exchange (ICE)	November 2004-February 2016
	Exchange rate	EUR/GBP	Bank of England	November 2004-February 2016
Netherlands	Electricity base load	EUR/MWh	Datastream/APX	January 2004-April 2016
	Electricity peak load	EUR/MWh	Datastream/APX	May 2009-April 2016
	Gas	EUR/MWh	Platts/Intercontinental Exchange (ICE)	January 2004-April 2016
Germany	Electricity	EUR/MWh	EEX	January 2004-December 2015 (monthly electricity futures)
				March 2010-December 2015 (weekly electricity futures)
	CO_2-EUAs	EUR/ tonne	EEX/Intercontinental Exchange (ICE)	March 2008-December 2015

Table 2. Standard deviation of the bases

The variables appearing in the heading of each row correspond, respectively, to the basis, that is the futures price minus the spot price, of the following variables: electricity base load; electricity peak load; natural gas; CO_2; clean spark spread for the base load; clean spark spread for the peak load; spark spread for the base load and spark spread of the peak load. Data is taken at weekly frequency for the period March 2008 to December 2015.

Basis	UK	Netherlands	Germany
$F_t^{e,base} - S_t^{e,base}$	8.49	5.82	6.67
$F_t^{e,peak} - S_t^{e,peak}$	15.28	4.56	7.93
$F_t^{g} - S_t^{g}$	3.38	1.33	1.19
$F_t^{co2} - S_t^{co2}$	0.19	0.19	0.19
$F_t^{cs,base} - S_t^{cs,base}$	7.51	5.46	6.91
$F_t^{cs,peak} - S_t^{cs,peak}$	14.14	4.67	10.48
$F_t^{s,base} - S_t^{s,base}$	7.51	5.47	6.91
$F_t^{s,peak} - S_t^{s,peak}$	14.14	4.66	10.46

Table 3. Summary statistics of price returns and basis returns of the CO_2

Variables appearing in the heading of each column correspond, respectively, to the realised returns of the spot, futures, and basis for CO_2. Note that basis is defined as futures price minus spot price. The heading of the last rows symbolises the correlation coefficient between futures and spot returns. Futures returns are obtained considering that rollover in the next front annual contract is done at the end of the year. Data is taken at weekly frequency for the period March 2008 to December 2015.

	ΔS_t^{co2}	ΔF_t^{co2}	$(F_t^{co2}-S_t^{co2})-(F_{t-1}^{co2}-S_{t-1}^{co2})$
Mean	-0.18	-0.15	-0.01
S.D.	1.50	1.47	0.21
Skewness	-1.30	-1.24	0.04
Excess Kurtosis	0.28	0.29	-1.03
$\rho(\Delta F_t^{co2}, \Delta S_t^{co2})$	0.99		

Table 4. Summary statistics of price returns

The ten variables appearing in the heading of each column correspond, respectively, to the realised returns of the following prices: electricity peak load spot; electricity peak load futures; electricity base load spot; electricity base load futures; natural gas spot; natural gas futures; spot peak load spark spread; futures peak load spark spread; spot base load spark spread and futures base load spark spread.

	Electricity				Natural Gas		Spark Spread			
	$\Delta S_t^{e,peak}$	$\Delta F_t^{e,peak}$	$\Delta S_t^{e,base}$	$\Delta F_t^{e,base}$	ΔS_t^{g}	ΔF_t^{g}	$\Delta S_t^{s,peak}$	$\Delta F_t^{s,peak}$	$\Delta S_t^{s,base}$	$\Delta F_t^{s,base}$
Panel A. One week variations. UK.										
Mean	-0.0820	-0.1773	-0.0434	-0.2004	-0.0600	-0.4446	-0.0412	0.1250	-0.0026	0.1019
S.D.	8.4190	4.2775	5.7225	2.8098	4.5461	2.3161	8.3674	4.1064	5.8468	2.5858
Skewness	-0.7086	-2.7216	-0.7326	-2.1702	-0.5316	-0.3422	-0.3386	-0.9092	-0.1354	0.3972
Excess Kurtosis	8.6899	42.9220	10.4136	29.1232	8.2866	2.6373	6.2070	42.9726	5.6145	36.8345
Panel B. One week variations. Netherlands.										
Mean	-0.0329	-0.4253	-0.0152	-0.3264	0.0043	-0.1588	-0.0483	-0.2573	-0.0238	-0.0089
S.D.	5.0101	3.0810	9.3041	2.5254	1.9548	0.9382	5.2070	2.8538	9.3158	2.3000
Skewness	1.0351	-0.5919	0.6853	0.1451	-0.3385	-0.2941	0.7815	-1.0190	0.6732	0.9433
Excess Kurtosis	14.4183	14.2115	13.0742	4.9142	25.8294	2.6949	11.4026	16.916	10.9578	6.8641
Panel C. One week variations. Germany.										
Mean	-0.0517	-0.2258	-0.0428	-0.3177	0.0065	-0.0728	-0.0630	-0.0806	-0.0558	-0.1722
S.D.	6.1352	4.8144	5.9784	3.6037	1.0827	0.7120	6.4357	4.3023	6.2325	3.1490
Skewness	-0.1823	-0.0534	-1.3282	-0.6636	0.0639	0.1324	-0.1185	-0.1093	-1.0178	-0.8061
Excess Kurtosis	4.6578	3.4092	11.4195	4.6611	5.5599	1.9377	4.6963	3.4761	8.7927	4.9237
Panel D. One month variations. UK.										
Mean	-0.3048	-0.6911	-0.1641	-0.8849	-0.1806	-1.7869	-0.1820	0.5240	-0.0413	0.3301
S.D.	7.0149	7.6105	5.4680	5.0392	6.0925	4.9154	5.7031	6.5098	4.3768	3.6865
Skewness	0.0601	-2.8583	0.3746	-2.3622	-0.4388	-0.5398	0.3232	-1.6235	0.5855	-0.5912
Excess Kurtosis	3.3801	21.9359	3.8945	16.543	7.0572	1.6742	3.3137	17.8530	2.9788	14.7833
Panel E. One month variations. Netherlands.										
Mean	-0.1062	-1.9034	0.8798	-2.1526	0.2321	-0.7288	-0.1434	-1.1351	-0.0601	-0.0393
S.D.	5.8143	5.5026	12.0543	8.3805	3.0897	2.5794	6.2940	4.7429	9.2318	5.0642
Skewness	0.1646	-0.7869	-0.1496	-0.0379	-0.4187	-0.7642	0.5746	-0.3462	0.0725	0.4477
Excess Kurtosis	1.2588	3.3061	0.2204	0.0684	0.6843	0.9798	2.9214	3.8289	3.4044	3.0555
Panel F. One month variations. Germany.										
Mean	0.011	-1.8905	0.004	-1.0206	0.0178	-0.7052	-0.0246	-0.4801	-0.0317	0.3899
S.D.	10.2835	8.4325	7.6476	5.1254	2.9268	2.2479	10.7682	7.4066	8.7126	4.6006
Skewness	0.6787	-0.1181	0.4249	-0.0846	-0.513	-1.1008	0.2441	0.2506	0.1339	0.0522
Excess Kurtosis	2.3577	2.6059	1.4149	1.6097	3.6752	2.7173	1.8969	3.0198	1.3354	1.5544

Table 5. Correlation matrix of the spot, futures and spark spread realised returns

For a sample size of T observations, the asymptotic distribution of the $\sqrt{T}$ times the correlation coefficient is a zero-one normal distribution. Those coefficients not significantly different to zero at 5% of significance level are marked with an asterisk (*). The variables appearing in the heading of each row and columns are described in Table 4.

	$\Delta S_t^{e,peak}$	$\Delta F_t^{e,peak}$	$\Delta S_t^{e,base}$	$\Delta F_t^{e,base}$	ΔS_t^{g}	ΔF_t^{g}	$\Delta S_t^{s,peak}$	$\Delta F_t^{s,peak}$	$\Delta S_t^{s,base}$	$\Delta F_t^{s,base}$
Panel (A). One-week variations. UK.										
$\Delta S_t^{e,peak}$	1,00									
$\Delta F_t^{e,peak}$	0.29	1.00								
$\Delta S_t^{e,base}$	0.97	0.32	1.00							
$\Delta F_t^{e,base}$	0.26	0.92	0.30	1.00						
ΔS_t^{g}	0.20	(*)0.08	0.23	0.17	1.00					
ΔF_t^{g}	0.25	0.29	0.26	0.42	0.53	1.00				
$\Delta S_t^{s,peak}$	0.93	0.26	0.90	0.20	-0.17	0.06	1.00			
$\Delta F_t^{s,peak}$	0.20	0.93	0.23	0.79	-0.13	(*)-0.09	0.25	1.00		
$\Delta S_t^{s,base}$	0.85	0.27	0.86	0.20	-0.30	(*)-0.02	0.96	0.29	1.00	
$\Delta F_t^{s,base}$	0.12	0.82	0.16	0.83	-0.14	-0.16	0.18	0.91	0.23	1.00
Panel (B). One-week variations. Netherlands.										
$\Delta S_t^{e,peak}$	1.00									
$\Delta F_t^{e,peak}$	0.10	1.00								
$\Delta S_t^{e,base}$	0.98	0.08	1.00							
$\Delta F_t^{e,base}$	0.21	0.22	0.22	1.00						
ΔS_t^{g}	0.19	0.11	0.21	0.24	1.00					
ΔF_t^{g}	0.06	0.19	0.08	0.50	0.55	1.00				
$\Delta S_t^{s,peak}$	0.95	(*) 0.07	0.93	0.14	-0.11	-0.11	1.00			
$\Delta F_t^{s,peak}$	(*) 0.05	0.81	0.03	(*)-0.10	-0.23	-0.43	0.13	1.00		
$\Delta S_t^{s,base}$	0.90	(*) 0.03	0.91	0.12	-0.21	-0.16	0.98	0.13	1.00	
$\Delta F_t^{s,base}$	0.18	(*) 0.08	0.18	0.70	-0.20	-0.28	0.25	0.24	0.26	1.00
Panel (C). One-week variations. Germany										
$\Delta S_t^{e,peak}$	1.00									
$\Delta F_t^{e,peak}$	0.28	1.00								
$\Delta S_t^{e,base}$	0.94	0.27	1.00							
$\Delta F_t^{e,base}$	0.27	0.95	0.30	1.00						
ΔS_t^{g}	(*) 0.08	0.34	(*) 0.06	0.34	1.00					
ΔF_t^{g}	0.14	0.49	0.12	0.50	0.62	1.00				
$\Delta S_t^{s,peak}$	0.93	0.16	0.88	0.15	-0.27	(*)-0.07	1.00			
$\Delta F_t^{s,peak}$	0.27	0.96	0.26	0.90	0.18	0.22	0.21	1.00		
$\Delta S_t^{s,base}$	0.88	0.14	0.94	0.17	-0.29	(*)-0.10	0.94	0.19	1.00	
$\Delta F_t^{s,base}$	0.25	0.87	0.29	0.92	(*) 0.10	0.12	0.21	0.93	0.24	1.00

Panel (D). One-month variations. UK.

	$\Delta S_t^{e,peak}$	$\Delta F_t^{e,peak}$	$\Delta S_t^{e,base}$	$\Delta F_t^{e,base}$	ΔS_t^{g}	ΔF_t^{g}	$\Delta S_t^{s,peak}$	$\Delta F_t^{s,peak}$	$\Delta S_t^{s,base}$	$\Delta F_t^{s,base}$
$\Delta S_t^{e,peak}$	1.00									
$\Delta F_t^{e,peak}$	0.39	1.00								
$\Delta S_t^{e,base}$	0.96	0.45	1.00							
$\Delta F_t^{e,base}$	0.47	0.93	0.55	1.00						
ΔS_t^{g}	0.58	0.22	0.62	0.40	1.00					
ΔF_t^{g}	0.50	0.52	0.53	0.69	0.57	1.00				
$\Delta S_t^{s,peak}$	0.81	0.32	0.74	0.29	(*)-0.01	0.20	1.00			
$\Delta F_t^{s,peak}$	(*) 0.18	0.89	0.24	0.72	(*)-0.05	(*) 0.07	0.26	1.00		
$\Delta S_t^{s,base}$	0.65	0.36	0.67	0.32	(*)-0.18	(*) 0.13	0.93	0.35	1.00	
$\Delta F_t^{s,base}$	(*) 0.17	0.79	0.25	0.72	(*) 0.00	(*)-0.01	0.21	0.93	0.31	1.00

Panel (E). One-month variations. Netherlands.

$\Delta S_t^{e,peak}$	1.00									
$\Delta F_t^{e,peak}$	0.46	1.00								
$\Delta S_t^{e,base}$	0.92	0.38	1.00							
$\Delta F_t^{e,base}$	0.45	0.65	0.50	1.00						
ΔS_t^{g}	0.34	0.33	0.28	0.43	1.00					
ΔF_t^{g}	0.42	0.55	0.43	0.78	0.61	1.00				
$\Delta S_t^{s,peak}$	0.65	0.16	0.62	0.07	-0.50	(*)-0.11	1.00			
$\Delta F_t^{s,peak}$	0.27	0.84	0.17	0.27	(*)-0.01	(*) 0.00	0.26	1.00		
$\Delta S_t^{s,base}$	0.41	(*) 0.00	0.52	(*) 0.00	-0.67	-0.21	0.92	(*) 0.13	1.00	
$\Delta F_t^{s,base}$	(*) 0.09	0.23	(*) 0.15	0.43	-0.22	-0.23	0.25	0.42	0.31	1.00

Panel (F). One-month variations. Germany

$\Delta S_t^{e,peak}$	1,00									
$\Delta F_t^{e,peak}$	0,49	1,00								
$\Delta S_t^{e,base}$	0,97	0,46	1,00							
$\Delta F_t^{e,base}$	0,49	0,96	0,49	1,00						
ΔS_t^{g}	0,20	0,45	0,19	0,45	1,00					
ΔF_t^{g}	(*) 0,14	0,51	0,17	0,57	0,55	1,00				
$\Delta S_t^{s,peak}$	0,85	0,23	0,83	0,23	-0,35	-0,17	1,00			
$\Delta F_t^{s,peak}$	0,49	0,84	0,43	0,76	0,17	(*)-0,04	0,37	1,00		
$\Delta S_t^{s,base}$	0,72	(*) 0,10	0,75	(*) 0,12	-0,51	-0,22	0,96	0,26	1,00	
$\Delta F_t^{s,base}$	0,42	0,57	0,38	0,55	(*)-0,05	-0,37	0,43	0,90	0,37	1,00

Table 6. Weekly cross-lagged correlations between natural gas and electricity returns

The first-order cross-correlation coefficient between two standardised data series x and y is estimated as $\rho(x_t, y_{t-1}) = \sum x_t y_{t-1} / \sqrt{\sum x_t^2 \sum y_t^2}$ of y with respect x. For a sample size of T observations, the asymptotic distribution of the $\sqrt{T}$ times the cross-correlation coefficient is a zero-one normal distribution, that is $\sqrt{T}\rho(x_t, y_{t-k}) \to AN(0,1)$ (see Cheung and Ng (1996) for more details). *, ** and ***, indicates significance at the 1%, 5% and 10% levels, respectively. The variables appearing in the heading of each row are described in Table 4.

	UK	***Netherlands***	***Germany***
$\rho(\Delta S_t^{e,base}, \Delta S_{t-1}^{g})$	*0.31	*0.18	*0.29
$\rho(\Delta S_t^{e,peak}, \Delta S_{t-1}^{g})$	*0.25	*0.15	*0.31
$\rho(\Delta F_t^{e,base}, \Delta S_{t-1}^{g})$	0.07	**0.09	0.05
$\rho(\Delta F_t^{e,peak}, \Delta S_{t-1}^{g})$	0.04	0.04	0.09
$\rho(\Delta S_t^{e,base}, \Delta F_{t-1}^{g})$	*0.14	*0.18	**0.12
$\rho(\Delta S_t^{e,peak}, \Delta F_{t-1}^{g})$	***0.09	*0.17	**0.14
$\rho(\Delta F_t^{e,base}, \Delta F_{t-1}^{g})$	0.07	0.12	-0.09
$\rho(\Delta F_t^{e,peak}, \Delta F_{t-1}^{g})$	0.06	0.06	-0.06
$\rho(\Delta S_t^{g}, \Delta S_{t-1}^{e,base},)$	*-0.17	-0.01	-0.04
$\rho(\Delta S_t^{g}, \Delta S_{t-1}^{e,peak})$	*-0.14	0.00	-0.06
$\rho(\Delta S_t^{g}, \Delta F_{t-1}^{e,base})$	*-0.14	**0.08	0.03
$\rho(\Delta S_t^{g}, \Delta F_{t-1}^{e,peak})$	**-0.13	-0.01	0.06
$\rho(\Delta F_t^{g}, \Delta S_{t-1}^{e,base},)$	-0.02	0.02	0.03
$\rho(\Delta F_t^{g}, \Delta S_{t-1}^{e,peak})$	-0.03	0.03	-0.01
$\rho(\Delta F_t^{g}, \Delta F_{t-1}^{e,base})$	-0.08	***0.07	-0.04
$\rho(\Delta F_t^{g}, \Delta F_{t-1}^{e,peak})$	**-0.10	-0.05	-0.06

Table 7. The basis as a predictor of spot, futures, and spark spread returns.

This table reports the results for the whole sample period of the regression between energy price changes appearing in the first column on the corresponding basis value at the beginning of the time interval appearing in the second column. The variables appearing in the first and second columns are described in Table 4. Between brackets *t*-statistic values computed with Newey-West standard errors are reported. Significant coefficients at 1%, 5% and 10% of significance level are highlighted with one (*), two (**) and three (***) asterisks, respectively.

Panel A. Netherlands.

		Weekly returns			Monthly returns		
Dependent variable	Basis	Intercept	Basis coefficient	Adjusted R^2	Intercept	Basis coefficient	Adjusted R^2
$\Delta S_t^{e,peak}$	$F_t^{e,peak} - S_t^{e,peak}$	-0.13 (-0.55)	0.55 (6.64)*	29.39%	0.47 (1.29)	0.64 (3.35)*	30.47%
$\Delta F_t^{e,peak}$	$F_t^{e,peak} - S_t^{e,peak}$	-0.43 (-2.89)*	0.04 (0.68)	0.47%	-1.87 (-3.27)*	0.03 (0.33)	0.08%
$\Delta S_t^{e,base}$	$F_t^{e,base} - S_t^{e,base}$	-0.31 (-1.75)***	0.35 (7.92)*	17.58%	-0.84 (-1.35)	0.62 (5.14)*	24.32%
$\Delta F_t^{e,base}$	$F_t^{e,base} - S_t^{e,base}$	-0.09 (-1.11)	-0.05 (-2.33)**	2.32%	-1.01 (-1.98)**	-0.33 (-3.97)*	12.19%
ΔS_t^{g}	$F_t^{g} - S_t^{g}$	-0.01 (-0.20)	0.23 (2.37)**	5.95%	-0.23 (-0.99)	0.94 (6.42)*	22.96%
ΔF_t^{g}	$F_t^{g} - S_t^{g}$	-0.07 (-1.93)***	-0.12 (-3.79)*	4.19%	-0.61 (-2.65)*	-0.34 (-1.64)***	5.44%
$\Delta S_t^{s,peak}$	$F_t^{s,peak} - S_t^{s,peak}$	-0.04 (-0.22)	0.66 (8.01)*	35.56%	0.55 (1.61)	0.75 (5.69)*	44.43%
$\Delta F_t^{s,peak}$	$F_t^{s,peak} - S_t^{s,peak}$	-0.26 (-1.99)**	0.07 (1.12)	1.29%	-1.03 (-1.97)**	0.11 (1.61)	1.71%
$\Delta S_t^{s,base}$	$F_t^{s,base} - S_t^{s,base}$	-0.45 (-1.26)	0.52 (6.21)*	24.63%	-0.72 (-1.22)	0.86 (8.19)*	39.21%
$\Delta F_t^{s,base}$	$F_t^{s,base} - S_t^{s,base}$	0.02 (0.22)	-0.03 (-2.38)*	1.86%	0.07 (0.17)	-0.15 (-2.33)**	3.75%

Panel B. Germany.

$\Delta S_t^{e,peak}$	$F_t^{e,peak} - S_t^{e,peak}$	-3.18 (-9.88)*	0.68 (11.78)*	60.68%	-4.78 (-5.36)*	0.63 (4.82)*	29.20%
$\Delta F_t^{e,peak}$	$F_t^{e,peak} - S_t^{e,peak}$	-0.36 (-0.85)	0.03 (0.45)	0.19%	-0.34 (-0.41)	-0.20 (-1.67)***	4.53%
$\Delta S_t^{e,base}$	$F_t^{e,base} - S_t^{e,base}$	-0.27 (-1.39)	0.79 (9.58)*	59.78%	-1.33 (-3.21)*	0.89 (6.81)*	43.52%
$\Delta F_t^{e,base}$	$F_t^{e,base} - S_t^{e,base}$	-0.32 (-1.56)	0.01 (0.10)	0.01%	-0.86 (-1.87)***	-0.11 (-0.98)	1.42%
ΔS_t^{g}	$F_t^{g} - S_t^{g}$	-0.01 (-0.09)	0.19 (2.19)**	4.98%	-0.19 (-0.85)	0.91 (6.12)*	20.45%
ΔF_t^{g}	$F_t^{g} - S_t^{g}$	-0.06 (-1.60)	-0.14 (-4.41)*	5.45%	-0.61 (-2.64)*	-0.39 (-1.98)**	6.61%
$\Delta S_t^{s,peak}$	$F_t^{s,peak} - S_t^{s,peak}$	-2.85 (-8.27)*	0.62 (10.64)*	51.31%	-5.75 (-7.26)*	0.80 (8.35)*	42.78%
$\Delta F_t^{s,peak}$	$F_t^{s,peak} - S_t^{s,peak}$	-0.23 (-0.65)	0.03 (0.66)	0.36%	0.14 (0.19)	-0.09 (-0.97)	1.05%
$\Delta S_t^{s,base}$	$F_t^{s,base} - S_t^{s,base}$	-0.18 (-0.72)	0.73 (9.34)*	52.51%	-1.13 (-2.54)**	1.07 (13.07)*	54.14%
$\Delta F_t^{s,base}$	$F_t^{s,base} - S_t^{s,base}$	-0.17 (-0.93)	0.01 (0.14)	0.02%	0.43 (1.00)	-0.04 (-0.71)	0.32%

Panel C. United Kingdom.

$\Delta S_t^{e,peak}$	$F_t^{e,peak} - S_t^{e,peak}$	-0.79 (-2.19)**	0.17 (1.42)	5.84%	-0.66 (-1.12)	0.09 (0.57)	1.62%
$\Delta F_t^{e,peak}$	$F_t^{e,peak} - S_t^{e,peak}$	0.16 (0.82)	-0.08 (-1.53)	5.17%	0.66 (0.69)	-0.33 (-1.99)**	19.48%
$\Delta S_t^{e,base}$	$F_t^{e,base} - S_t^{e,base}$	-0.44 (-2.6)*	0.26 (1.87)***	8.85%	-0.52 (-1.36)	0.25 (0.96)	5.62%
$\Delta F_t^{e,base}$	$F_t^{e,base} - S_t^{e,base}$	-0.04 (-0.32)	-0.10 (-1.88)***	5.96%	-0.47 (-0.81)	-0.29 (-1.20)	8.75%
ΔS_t^{g}	$F_t^{g} - S_t^{g}$	-0.21 (-1.03)	0.32 (3.59)*	10.46%	-0.32 (-0.57)	0.52 (1.54)	9.48%
ΔF_t^{g}	$F_t^{g} - S_t^{g}$	-0.39 (-3.49)*	-0.10 (-4.69)*	4.29%	-1.66 (-2.71)*	-0.44 (-2.69)*	10.29%
$\Delta S_t^{s,peak}$	$F_t^{s,peak} - S_t^{s,peak}$	-0.91 (-2.39)**	0.22 (1.59)	8.17%	-0.65 (-1.66)***	0.12 (0.83)	3.67%
$\Delta F_t^{s,peak}$	$F_t^{s,peak} - S_t^{s,peak}$	0.38 (2.11)**	-0.06 (-1.12)	2.86%	1.19 (1.59)	-0.17 (-0.93)	5.62%
$\Delta S_t^{s,base}$	$F_t^{s,base} - S_t^{s,base}$	-0.53 (-3.58)*	0.43 (2.94)*	16.18%	-0.56 (-2.53)**	0.43 (2.24)**	19.83%
$\Delta F_t^{s,base}$	$F_t^{s,base} - S_t^{s,base}$	0.20 (1.74)***	-0.08 (-1.61)	2.94%	0.29 (0.90)	0.03 (0.18)	0.12%

Table 8. Spark spread risk hedging effectiveness.

This table displays the risk reduction achieved by each hedging strategy described in Section 2. The *in-sample* results are computed for the first five years in weekly hedges and about ten years for monthly hedges, then a moving window is used to compute the *out-of-sample* results. In the second row of each panel, the unhedged spot position variance is reported and constitutes the base for calculating the risk reduction achieved with each hedging strategy. This variance is as $VAR\left[\Delta S_t - \hat{\lambda}(F_t - S_t)\right]$ following the Ederington and Salas (2008) approach. The variance of each hedging strategy is computed with equation (5). *Ex-ante* hedging ratios for the period [*t*–1,*t*] are estimated using the information available until *t*–1, and the model is estimated again each time the moving window sample moves ahead. Those strategies with the largest risk reduction are indicated with an asterisk (*)

		Weekly hedges				**Monthly hedges**			
		In-Sample		Out-sample		In-Sample		Out-Sample	
Hedging strategy		Base	Peak	Base	Peak	Base	Peak	Base	Peak
				Panel (A). Germany					
		Mar.10–Dec.15				Jan.04 – Apr.12		May.12 – Dec.15	
$\beta_t^e = \beta_t^g = 0$		18.44	20.17			38.39	81.41	26.63	27.81
				Risk reduction (%)					
$\beta_t^e = \beta_t^g = 1$		-5.40	-5.40			30.39	19.83	48.90*	43.38*
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	10.84	-45.65			36.21	33.20	39.69	29.80
	with basis	10.87	5.42			36.46	34.02*	41.05	34.62
β_t^e and β_t^g separately	w/o basis	16.66	10.85			36.45	33.06	40.72	36.81
	with basis	17.65	11.59			34.77	29.71	46.61	42.20
β_t^e and β_t^g jointly	w/o basis	34.47	32.45			33.95	25.21	40.68	37.43
	with basis	34.75*	33.02*			36.67*	34.29	41.67	33.24
				Panel (B). Netherlands					
		Jan.04–Dec.08	May.09–Apr.14	Jan.08–Apr.16	Apr.14–Apr.16	Jan.04–May.12	May.09–Apr.16	Jun.12–Apr.16	
$\beta_t^e = \beta_t^g = 0$		141.14	20.55	13.83	9.76	69.75	22.03	17.00	
				Risk reduction (%)					
$\beta_t^e = \beta_t^g = 1$		14.64	5.47	9.71	12.85	37.76	-54.53	17.01	
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	15.56	15.39	8.59	8.41	35.33	4.29	15.38	
	with basis	16.38*	16.53	7.40	7.98	38.81	5.56	14.74	
β_t^e and β_t^g separately	w/o basis	15.23	18.36	23.64*	13.03	34.46	29.46	23.09	
	with basis	16.37	18.22	20.62	10.40	38.77	32.15*	17.52	
β_t^e and β_t^g jointly	w/o basis	12.56	30.73	22.81	16.46*	30.16	5.45	28.92*	
	with basis	13.25	30.88*	18.67	16.02	39.17*	6.78	13.61	
				Panel (C). UK.					
		Nov.07 – Nov.12		Nov.12 – Feb.16		Nov.07 – Feb.16			
$\beta_t^e = \beta_t^g = 0$		40.86	94.30	9.57	17.87	14.39	29.38		
				Risk reduction (%)					
$\beta_t^e = \beta_t^g = 1$		10.78	8.15	1.09	-12.02	-16.65	-35.18		
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	12.44	11.44	2.08	-2.37	15.64	18.60		
	with basis	13.17	11.76	1.04	-4.46	15.65	18.95		
β_t^e and β_t^g separately	w/o basis	8.55	7.72	2.43	-3.08	6.54	3.42		
	with basis	7.69	7.06	4.31	-5.36	-5.68	-3.17		
β_t^e and β_t^g jointly	w/o basis	12.9	13.36	4.52*	-2.64	19.58	24.40		
	with basis	13.68*	13.70*	3.60	-14.56	20.05*	25.50*		

Table 9. Hedging effectiveness in Electricity and Natural Gas Prices.

This table is similar to Table 8 but applying each hedging strategy in individual hedges on electricity (Base and peak) and Natural Gas.

Panel (A). Germany.

Hedging strategy	**Weekly hedges**					
	In-Sample			Out-sample		
	Base	Peak	Natural gas	Base	Peak	Natural gas
	Mar.10–Dec.15					
Spot variance	14.37	14.81	1.15			
	Risk reduction (%)			Risk reduction (%)		
Naïve (*b*=1)	14.36	-52.62	52.01			
OLS w/o basis	20.92	15.67	51.50			
OLS with basis	20.94*	15.95*	52.35*			

Hedging strategy	**Monthly hedges**					
	In-Sample			Out-sample		
	Base	Peak	Natural gas	Base	Peak	Natural gas
	Jan.04 – Apr.12			May.12 – Dec.15		
Spot variance	41.68	102.00	5.12	14.11	16.18	8.11
	Risk reduction (%)			Risk reduction (%)		
Naïve (*b*=1)	58.69	53.38	68.61	60.35*	55.89*	61.77*
OLS w/o basis	58.80	54.89	65.00	51.00	47.58	51.58
OLS with basis	60.00*	58.12*	69.10*	55.65	53.15	59.15

Panel (B). Netherlands.

Hedging strategy	**Weekly hedges**					
	In-Sample			Out-sample		
	Base	Peak	Natural gas	Base	Peak	Natural gas
	Jan.04–Dec.08	May.09–Apr.14	Jan.04–Dec.08	Jan.08–Apr.16	Apr.14–Apr.16	Jan.08–Apr.16
Spot variance	150.27	20.91	6.31	12.82	10.24	1.41
	Risk reduction (%)			Risk reduction (%)		
Naïve (*b*=1)	11.98	11.57	39.53	0.39	11.75	53.01
OLS w/o basis	12.00	19.86	43.73	0.28	12.09	51.98
OLS with basis	12.56*	21.43	44.55	-3.72	11.16	50.43

Hedging strategy	**Monthly hedges**					
	In-Sample			Out-sample		
	Base	Peak	Natural gas	Base	Peak	Natural gas
	Jan.04–May.12	May.09–Apr.16	Jan.04–May.12	Jun.12–Apr.16		Jun.12–Apr.16
Spot variance	77.19	23.51	7.76	8.81		6.38
	Risk reduction (%)			Risk reduction (%)		
Naïve (*b*=1)	58.42	-1.95	68.62	64.86		56.54
OLS w/o basis	50.21	31.19	65.40	62.30		46.52
OLS with basis	58.61	31.22	69.59	69.06*		52.97

Table 9. Hedging effectiveness in Electricity and Natural Gas Prices. (Continued).

Panel (C). UK.

	Weekly hedges					
	In-Sample			Out-sample		
Hedging strategy	Base	Peak	Natural gas	Base	Peak	Natural gas
	Nov. 14th, 2007 – Nov. 7th, 2012			Nov. 14th, 2012 – Feb. 10th, 2016		
Spot variance	43.98	92.65	24.90	10.40	16.29	9.60
	Risk reduction (%)			Risk reduction (%)		
Naïve (*b*=1)	14.66	8.20	43.59	6.01	-15.43	39.27
OLS w/o basis	15.39	11.37	44.35	6.06	-3.77	40.00
OLS with basis	16.09*	11.69*	45.51*	5.75	-5.97	41.19

	Monthly hedges					
	In-Sample			Out-sample		
Hedging strategy	Base	Peak	Natural gas	Base	Peak	Natural gas
	November 2007 – February 2016					
Spot variance	31.29	47.38	35.86			
	Risk reduction (%)			Risk reduction (%)		
Naïve (*b*=1)	44.60	16.63	61.16			
OLS w/o basis	46.86	33.70	58.03			
OLS with basis	48.69*	37.49*	61.30			

Table 10. Hedging effectiveness in Germany. Spark prices

This table is similar to Table 8 in the manuscript, but two more panels are added. Value at Risk (VaR) and Expected Shortfall (ES) are calculated at the 5% level for each strategy and are estimated using the historical simulation approach based on the empirical distributions or actual returns.

		WEEKLY		**MONTHLY**			
		In-Sample		**In-sample**		**Out-Sample**	
		Base Spark	Peak Spark	Base Spark	Peak Spark	Base Spark	Peak Spark
	Period	Mar.10–Dec.15		Jan.04 – Apr.12		May.12 – Dec.15	
Variance							
$\beta_t^e = \beta_t^g = 0$	Spot variance	18.44	20.17	38.39	81.41	26.63	27.81
		Risk reduction (%)		**Risk reduction (%)**		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		-5.40	-5.40	30.39	19.83	48.90	43.38*
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	10.84	-45.65	36.21	33.20	39.69	29.80
	with basis	10.87	5.42	36.46	34.02*	41.05	34.62
β_t^e and β_t^e separately	w/o basis	16.66	10.85	36.45	33.06	40.72	36.81
	with basis	17.65	11.59	34.77	29.71	46.61*	42.20
β_t^e and β_t^e jointly	w/o basis	34.47	32.45	33.95	25.21	40.68	37.43
	with basis	34.75*	33.02*	36.67*	34.29	41.67	33.24
Value at Risk							
$\beta_t^e = \beta_t^g = 0$	Spot VaR	-5.49	-8.94	-10.41	-22.69	-8.31	-11.18
		Risk reduction (%)		**Risk reduction (%)**		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		-24.00	-23.19	-7.81	6.50	27.63	8.34
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	-15.68	0.00	0.83	9.58	28.52	11.79
	with basis	-13.74	1.88	0.72	8.88	28.24	11.71
β_t^e and β_t^e separately	w/o basis	-2.66	2.64	-7.97	9.23	27.35	9.72
	with basis	-4.11	2.76	0.79	10.84	29.65	8.75
β_t^e and β_t^e jointly	w/o basis	-0.60	1.10	-4.34	1.49	27.11	6.53
	with basis	-0.60	3.07	2.68	10.08	18.59	12.28
Expected Shortfall							
$\beta_t^e = \beta_t^g = 0$	Spot ES	-10.68	-12.71	-16.85	-31.22	-12.87	-16.17
		Risk reduction (%)		**Risk reduction (%)**		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		3.94	-13.54	22.50	15.37	25.60	13.47
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	4.87	1.89	24.35	17.31	21.80	11.85
	with basis	4.69	1.86	24.52	18.79	20.32	11.89
β_t^e and β_t^e separately	w/o basis	7.05	3.10	22.55	17.11	24.56	12.83
	with basis	7.68	3.06	24.37	16.08	20.79	13.41
β_t^e and β_t^e jointly	w/o basis	7.90	2.89	23.83	10.02	22.19	14.08
	with basis	7.90	3.00	17.07	20.13	19.46	11.18

Table 11. Hedging effectiveness in the Netherlands. Spark prices

This table is similar to Table 10 for the Netherlands.

		WEEKLY				MONTHLY		
		In-Sample		**Out-sample**		**In-Sample**		**Out-sample**
		Base Spark	Peak Spark	Base Spark	Peak Spark	Base Spark	Peak Spark	Base Spark
	Period	Jan.04 – Dec.08	May.09 – Apr.14	Jan.08 – Apr.16	Apr.14 – Apr.16	Jan.04 – May.12	May.09– Apr.16	Jun.12– Apr.16
Variance								
$\beta_t^e = \beta_t^g = 0$	Spot variance	141.14	20.55	13.83	9.76	69.75	22.03	17.00
		Risk reduction (%)		**Risk reduction (%)**		**Risk reduction (%)**		
$\beta_t^e = \beta_t^g = 1$		14.64	5.47	9.71	12.85	37.76	-54.53	17.01
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	15.56	15.39	8.59	8.41	35.33	4.29	15.38
	with basis	16.38*	16.53	7.40	7.98	38.81	5.56	14.74
β_t^e and β_t^e separately	w/o basis	15.23	18.36	23.64*	13.03	34.46	29.46	23.09
	with basis	16.37	18.22	20.62	10.40	38.77	32.15*	17.52
β_t^e and β_t^e jointly	w/o basis	12.56	30.73	22.81	16.46*	30.16	5.45	28.92*
	with basis	13.25	30.88*	18.67	16.02	39.17*	6.78	13.61
Value at Risk								
$\beta_t^e = \beta_t^g = 0$	Spot VaR	-7.10	-6.99	-4.22	-3.65	-12.98	-4.78	-6.16
		Risk reduction (%)		**Risk reduction (%)**		**Risk reduction (%)**		
$\beta_t^e = \beta_t^g = 1$		2.59	10.05	18.58	15.29	16.95	-4.82	22.75
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	2.19	10.53	18.96	10.91	9.19	-0.36	25.21
	with basis	2.45	11.97	18.92	10.18	7.63	7.29	25.20
β_t^e and β_t^e separately	w/o basis	-3.50	12.75	20.51	7.33	16.56	-5.94	25.29
	with basis	-5.52	11.08	18.18	7.83	9.72	-14.16	28.43
β_t^e and β_t^e jointly	w/o basis	-3.39	14.13	12.69	13.70	15.51	-0.20	26.05
	with basis	0.00	8.39	14.98	9.15	-4.48	-0.20	20.37
Expected Shortfall								
$\beta_t^e = \beta_t^g = 0$	Spot ES	-9.44	-8.65	-4.99	-4.36	-18.04	-16.28	-10.46
		Risk reduction (%)		**Risk reduction (%)**		**Risk reduction (%)**		
$\beta_t^e = \beta_t^g = 1$		-2.41	-0.14	9.05	7.49	12.89	-2.40	2.82
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	-4.74	2.72	9.17	5.42	16.46	6.72	3.04
	with basis	-9.00	2.76	11.19	4.71	18.88	5.47	3.89
β_t^e and β_t^e separately	w/o basis	1.99	5.29	8.95	2.31	15.58	8.73	2.45
	with basis	0.64	5.79	6.61	-2.50	15.93	7.21	7.48
β_t^e and β_t^e jointly	w/o basis	-2.73	6.05	6.41	7.07	17.80	4.59	1.53
	with basis	-9.28	6.13	5.92	5.53	9.13	4.59	8.72

Table 12. Hedging effectiveness in the UK. Spark prices.

This table is similar to Table 10 for the UK

		WEEKLY				MONTHLY	
		In-Sample		**Out-sample**		**In-Sample**	
		Base Spark	Peak Spark	Base Spark	Peak Spark	Base Spark	Peak Spark
	Period	Nov.07 – Nov.12		Nov.12 – Feb.16		Nov.07 – Feb.16	
Variance							
$\beta_t^e = \beta_t^g = 0$	Spot variance	40.86	94.30	9.57	17.87	14.39	29.38
		Risk reduction (%)		**Risk reduction (%)**		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		10.78	8.15	1.09	-12.02	-16.65	-35.18
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	12.44	11.44	2.08	-2.37	15.64	18.60
	with basis	13.17	11.76	1.04	-4.46	15.65	18.95
β_t^e and β_t^e separately	w/o basis	8.55	7.72	2.43	-3.08	6.54	3.42
	with basis	7.69	7.06	4.31	-5.36	-5.68	-3.17
β_t^e and β_t^e jointly	w/o basis	12.9	13.36	4.52*	-2.64	19.58	24.40
	with basis	13.68*	13.70*	3.60	-14.56	20.05*	25.50*
Value at Risk							
$\beta_t^e = \beta_t^g = 0$	Spot VaR	-10.51	-18.67	-5.77	-8.08	-5.64	-9.16
		Risk reduction (%)		**Risk reduction (%)**		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		-9.57	-4.14	3.02	-1.01	-3.91	-29.81
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	-9.19	-0.14	3.76	-1.14	4.88	0.45
	with basis	-11.39	-1.77	3.19	-1.42	4.88	0.52
β_t^e and β_t^e separately	w/o basis	-20.16	4.38	1.96	-7.27	-7.49	1.22
	with basis	-21.99	3.55	3.20	-5.78	-1.68	-15.08
β_t^e and β_t^e jointly	w/o basis	-6.06	-3.63	0.52	-2.38	-16.45	-0.41
	with basis	-10.46	-5.91	2.52	1.60	-9.25	-0.98
Expected Shortfall							
$\beta_t^e = \beta_t^g = 0$	Spot ES	-18.48	-28.26	-7.00	-9.09	-10.94	-16.47
		Risk reduction (%)		**Risk reduction (%)**		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		-1.48	-2.40	-1.49	-12.34	-29.72	-40.14
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	1.55	1.15	-0.58	1.39	-3.98	-1.08
	with basis	0.83	0.33	-1.30	-4.72	4.04	-3.82
β_t^e and β_t^e separately	w/o basis	-3.36	-2.42	-1.07	-5.62	-21.92	-21.61
	with basis	-4.47	-3.88	-1.85	-8.55	-12.82	-32.69
β_t^e and β_t^e jointly	w/o basis	3.22	4.93	0.00	2.34*	10.92	9.99
	with basis	3.33	5.49	-0.56	-3.73	5.83	14.72

Table 13. Hedging effectiveness in Germany.

This table is similar to Table 10, but uses only spot and futures prices on base and peak load electricity and natural gas at weekly and monthly frequencies. Specifically, this table displays the risk reduction achieved by three hedging strategies applied to a single commodity: naïve; OLS without the basis; and OLS with the basis. That is, applying equations (8) and (9) to a single commodity. Variance of each hedging strategy is computed as $VAR\left[\Delta S_t^{e,base} - \hat{\beta}_t \Delta F_t^{e,base}\right]$ and $VAR\left[\Delta S_t^{e,base} - \hat{\beta}_t \Delta F_t^{e,base} - \hat{\lambda}(F_t^{e,base} - S_t^{e,base})\right]$ in the 'OLS w/o basis' and 'OLS with basis' approaches, respectively. Value at Risk (VaR) and Expected Shortfall (ES) are calculated at the 5% level and are estimated using the historical simulation approach based on the empirical distributions or actual returns.

In the sample	**WEEKLY**			**MONTHLY**		
	Base	**Peak**	**Natural Gas**	**Base**	**Peak**	**Natural Gas**
Period		Mar.10–Dec.15			Jan.04 – Apr.12	
Spot variance (not hedged)	14.37	14.81	1.15	41.68	102.00	8.11
Variance		**Risk reduction (%)**			**Risk reduction (%)**	
Naïve (*b*=1)	14.37	-52.62	52.01	58.69	53.38	68.61
OLS w/o basis	20.92	15.67	51.50	58.80	54.89	65.00
OLS with basis	20.94*	15.95*	52.35	60.00	58.12*	69.10
Value at Risk		**Risk reduction (%)**			**Risk reduction (%)**	
Naïve (*b*=1)	-3.20	-19.44	52.87	27.33	26.98	71.71
OLS w/o basis	6.03	5.55	50.63	35.77	31.58	57.47
OLS with basis	5.83	4.99	54.39*	30.14	33.19	71.88
Expected Shortfall		**Risk reduction (%)**			**Risk reduction (%)62.63**	
Naïve (*b*=1)	-5.08	-20.77	34.35	46.81	33.91	62.63
OLS w/o basis	6.97	5.26	33.22	43.29	30.12	49.63
OLS with basis	6.98	5.56	35.90	46.61	34.56	60.10

Out of the sample	**WEEKLY**			**MONTHLY**		
	Base	**Peak**	**Natural Gas**	**Base**	**Peak**	**Natural Gas**
Period					May.12 – Dec.15	
Spot variance (not hedged)				14.11	16.18	
Variance		**Risk reduction (%)**			**Risk reduction (%)**	
Naïve (*b*=1)				60.35*	55.89	61.77
OLS w/o basis				51.00	47.58	51.58
OLS with basis				55.65	53.15	59.15
Value at Risk		**Risk reduction (%)**			**Risk reduction (%)**	
Naïve (*b*=1)				49.67	43.51	88.06*
OLS w/o basis				41.81	20.11	67.65
OLS with basis				48.85	33.95	83.22
Expected Shortfall		**Risk reduction (%)**			**Risk reduction (%)**	
Naïve (*b*=1)				56.47	41.80	83.34
OLS w/o basis				41.16	29.57	64.34
OLS with basis				50.97	37.77	79.83

Table 14. Hedging effectiveness in the Netherlands.

This table is similar to Table 13 for the Netherlands.

In the sample	WEEKLY			MONTHLY		
	Base	Peak	Natural Gas	Base	Peak	Natural Gas
Period	Jan.04 – Dec.08	May.09 – Apr.14	Jan.04 – Dec.08	Jan.04 – May.12	May.09– Apr.16	Jan.04 – May.12
Spot variance (not hedged)	150.27	20.91	6.31	77.19	23.51	7.76
Variance		**Risk reduction (%)**			**Risk reduction (%)**	
Naïve (b=1)	11.98	11.57	39.53	58.42	-1.95	68.62
OLS w/o basis	12.00	19.86	43.73	50.21	31.19	65.40
OLS with basis	12.56*	21.43	44.55	58.61	31.22	69.59
Value at Risk		**Risk reduction (%)**			**Risk reduction (%)**	
Naïve (b=1)	1.69	10.93	43.27	45.54	51.07*	70.00
OLS w/o basis	1.73	11.08	45.06	40.56	30.78	55.33
OLS with basis	1.46	12.55	39.64	46.68	28.85	69.12
Expected Shortfall		**Risk reduction (%)**			**Risk reduction (%)**	
Naïve (b=1)	-3.85	8.19	25.72	38.07	48.99	65.44
OLS w/o basis	-3.95	12.70	29.37	34.70	49.56	50.43
OLS with basis	-9.62	14.53	27.89	39.39	48.71	61.75

Out of the sample	WEEKLY			MONTHLY		
	Base	Peak	Natural Gas	Base	Peak	Natural Gas
Period	Jan.08 – Apr.16	Apr.14 – Apr.16	Jan.08 – Apr.16	Jun.12– Apr.16		Jun.12– Apr.16
Spot variance (not hedged)	12.82	10.24	1.41	8.81		6.38
Variance		**Risk reduction (%)**			**Risk reduction (%)**	
Naïve (b=1)	0.39	11.75	53.01	64.86		56.54
OLS w/o basis	0.28	12.09	51.98	62.30		46.52
OLS with basis	-3.72	11.16	50.43	69.06*		52.97
Value at Risk		**Risk reduction (%)**			**Risk reduction (%)**	
Naïve (b=1)	1.19	21.63	63.12*	57.09		80.84*
OLS w/o basis	1.99	24.33	48.58	28.75		71.98
OLS with basis	4.58	22.16	40.32	57.49		77.02
Expected Shortfall		**Risk reduction (%)**			**Risk reduction (%)**	
Naïve (b=1)	11.53	25.25*	55.46	56.96		78.75
OLS w/o basis	11.29	20.12	51.75	42.45		64.57
OLS with basis	11.68	18.55	44.48	59.19		75.39

Table 15. Hedging effectiveness in the UK.

This table is similar to Table 13 for the UK.

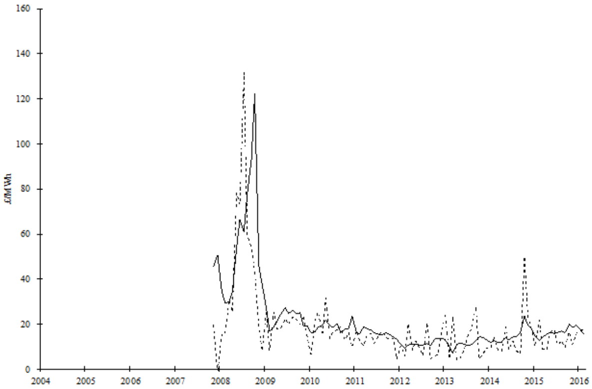
In the sample	WEEKLY			MONTHLY		
	Base	Peak	Natural Gas	Base	Peak	Natural Gas
Period	Nov. 14th, 2007 – Nov. 7th, 2012			November 2007 – February 2016		
Spot variance (not hedged)	43.98	92.65	24.90	31.29	47.38	35.86
Variance	**Risk reduction (%)**			**Risk reduction (%)**		
Naïve (*b*=1)	14.66	8.20	43.59	44.60	16.63	61.16
OLS w/o basis	15.39	11.37	44.35	46.86	33.70	58.03
OLS with basis	16.09*	11.69*	45.51*	48.69*	37.49*	61.30
Value at Risk	**Risk reduction (%)**			**Risk reduction (%)**		
Naïve (*b*=1)	-1.24	0.56	25.84	23.19	-6.61	71.68
OLS w/o basis	3.63	-0.24	26.62	27.56	-29.28	56.43
OLS with basis	5.44	-1.35	31.45	28.12	27.46	67.71
Expected Shortfall	**Risk reduction (%)**			**Risk reduction (%)**		
Naïve (*b*=1)	0.00	3.68	27.48	26.36	8.50	69.15
OLS w/o basis	1.31	3.52	28.66	26.31	16.16	60.71
OLS with basis	0.92	3.81	32.57	30.88	14.20	69.16*

Out of the sample	WEEKLY			MONTHLY		
	Base	Peak	Natural Gas	Base	Peak	Natural Gas
Period	Nov. 14th, 2012 – Feb. 10th, 2016					
Spot variance (not hedged)	10.40	16.29	9.60			
Variance	**Risk reduction (%)**			**Risk reduction (%)**		
Naïve (*b*=1)	6.01	-15.43	39.27			
OLS w/o basis	6.06	-3.77	40.00			
OLS with basis	5.75	-5.97	41.19			
Value at Risk	**Risk reduction (%)**			**Risk reduction (%)**		
Naïve (*b*=1)	6.95	7.13	40.96			
OLS w/o basis	8.48	-0.50	42.19			
OLS with basis	9.53	1.23	46.45			
Expected Shortfall	**Risk reduction (%)**			**Risk reduction (%)**		
Naïve (*b*=1)	11.33	-5.14	23.93			
OLS w/o basis	8.45	-2.55	24.24			
OLS with basis	10.20	-2.39	24.91			

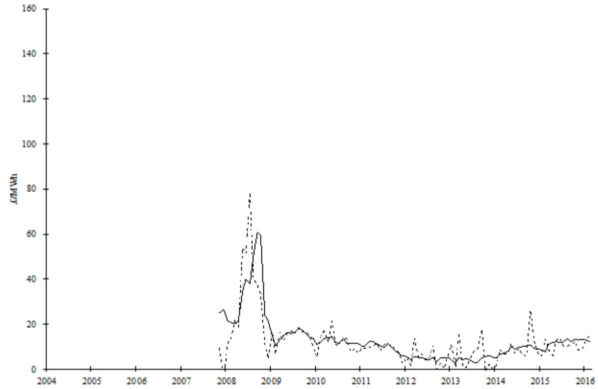
Annex II: Graphs

Figure 1. Futures and spot spark spreads.

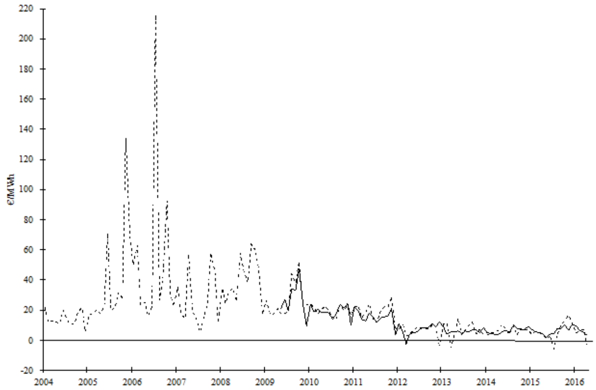
Futures (—) and spot (----) spark spreads



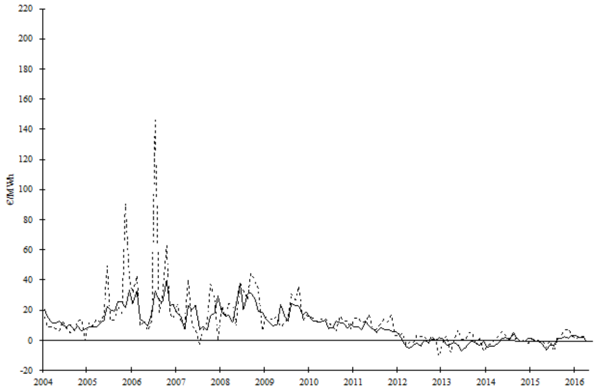
a) UK peak spark spread



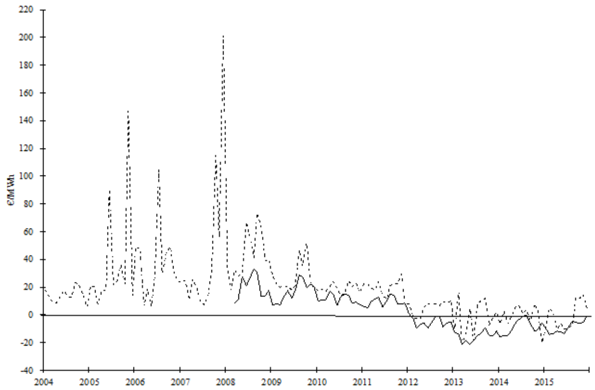
b) UK base spark spread



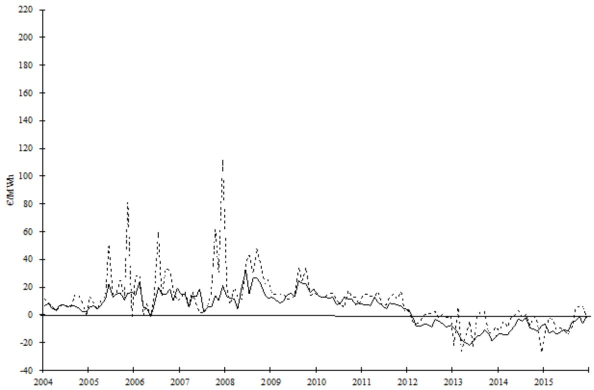
c) Netherlands peak spark spread



d) Netherlands base spark spread



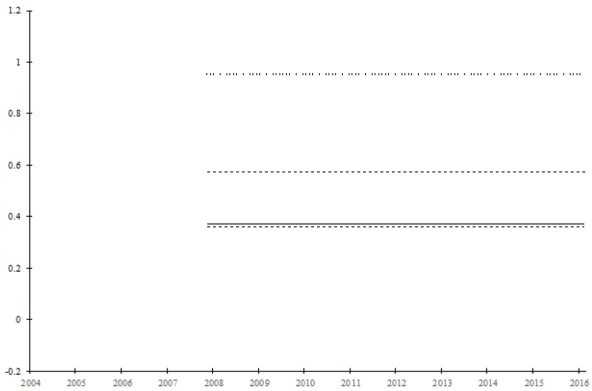
e) Germany peak spark spread



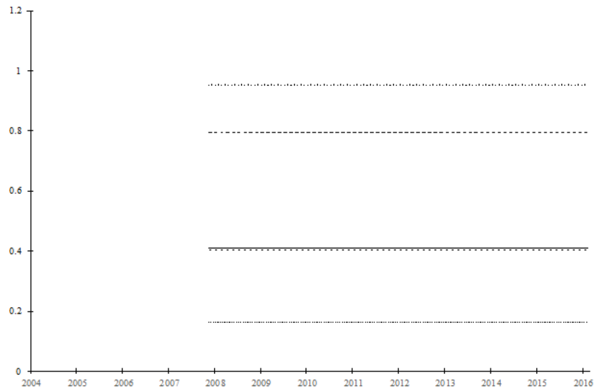
f) Germany base spark spread

Figure 2. Monthly spark spreads hedging ratios

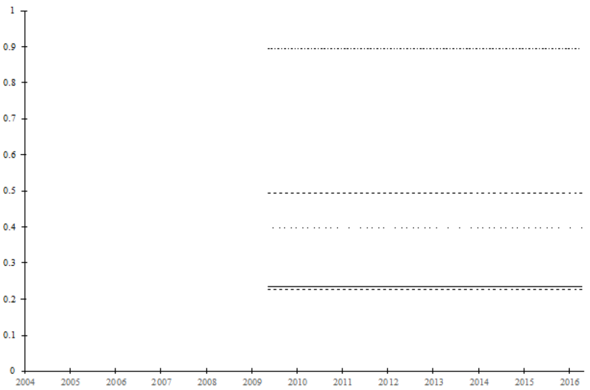
Following Ederington and Salas (2008), the estimated hedging ratios for electricity and natural gas futures corresponding to the following three cases are shown: (1) β_t^e (---) and (⋯) β_t^g are jointly obtained, (2) β_t^e (---) and β_t^g (⋯) are separately obtained in each market as independent problems, and (3) $\beta_t^e = \beta_t^g = \beta_t$ (—), jointly obtained but restricted to be equal.



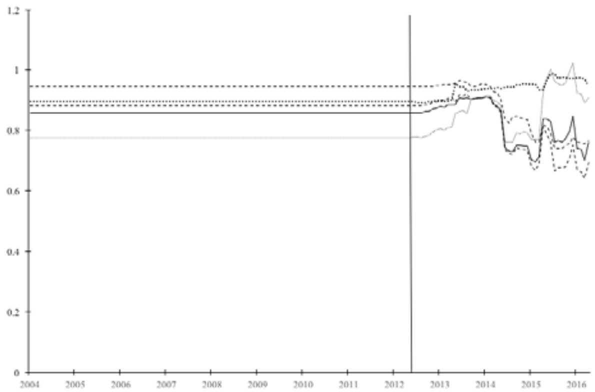
a) UK peak spark spread



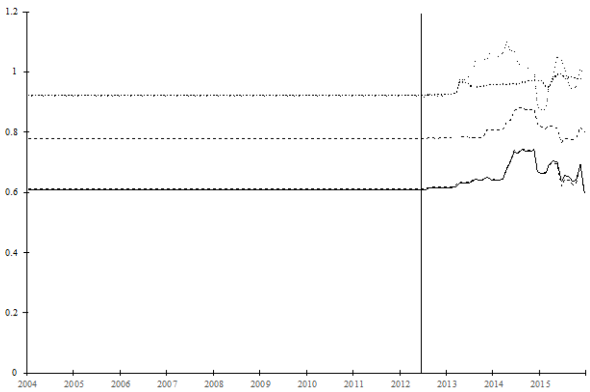
b) UK base spark spread



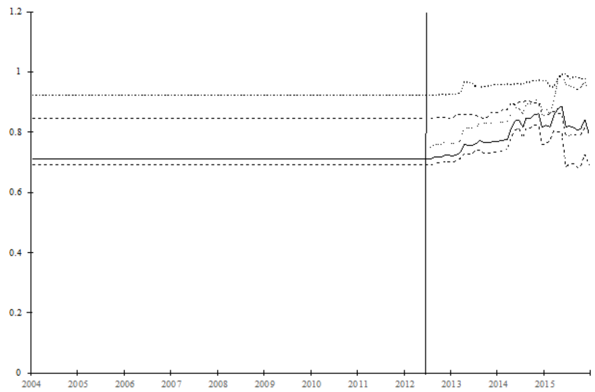
c) Netherlands peak spark spread



d) Netherlands base spark spread



e) Germany peak spark spread



f) Germany base spark spread

Conclusions

1. Conclusions

This PhD dissertation analyzes the influence of seasonality in several risk management strategies and its hedging performance. The dissertation also studies some asset pricing issues in the European natural gas. A study on the natural gas risk premium in natural gas futures contracts in the British market has been presented. Next are described the major and minor findings.

1.1 Major findings

I. The special statistical features of natural gas prices can produce very wrong computed risk reductions that can be corrected using the Ederington and Salas (2008) framework when considering the expected change in spot prices in the minimum variance approach. The use of this new approach enables a significant improvement on the effectiveness measures for hedging strategies. Hedging performance can also be significantly improved by increasing hedging duration.

II. Risk premiums in the UK natural gas futures are dominated by the ‘spot component’ (rollover risk premiums exceed conventional risk premiums), results similar to the ones of Szymanowska et al. (2014). We also found that seasonal patterns are detected in the studied risk premiums, winter months feature higher and more volatile risk premiums.

III. Spark spread returns can be partially anticipated and the Ederington and Salas (2008) framework should be applied, risk reduction is underestimated in the standard approach (Ederington, 1979) due to the existence of a seasonal pattern that can be subtracted from the total returns.

1.2 Minor findings

I. A strong seasonality exists in the volatility of spot and futures price returns which have been significantly higher in winter than in summer. This seasonality is taken into account in the analysed models. We have also found that improving statistical price modeling does not guarantee a better hedging performance.

II. Risk factors can explain time-varying realized risk premiums as predicted by the theory. Furthermore, liquidity seems to be the most explicative variable explaining the difference between the rollover and conventional risk premiums.

III. Spark spread and clean spark spread risk are two indistinguishable variables for risk management. We also find that hedging the spark spread with futures is more difficult than hedging electricity and natural gas price risks with their respective futures contracts.

2. Further research

The different issues in this PhD dissertation has covered several aspects of risk management and asset pricing in the energy markets. Nevertheless, some further research in both aspects could be done to continue the work began in this dissertation.

Concerning risk management in energy markets, an interesting and unexplored field would be the liquefied natural gas (LNG) market. The liquefied natural gas (LNG) industry has experienced remarkable growth in traded volume since the early 2000s, in the context of liberalization of electricity and gas industries, and an increase in demand for natural gas. Traditionally, a LNG project involves a bilateral long-term contract, normally with a 20-year duration, between a buyer and seller, to back up the initial investment. However, in the last years, contracting arrangements between buyers and sellers have become more flexible and there has been an ongoing shift towards trade in spot and short-term markets up to 25% of total LNG sales nowadays. The progressive substitution of long term oil indexed contracts to sales of LNG on the spot market and short-term contracts in a context of declining prices will have dramatic consequences for producers. In this uncertain context, it is of vital importance that industry players facing an exposure to LNG market prices could hedge it away. It could be test several cross-hedging strategies based on international futures contracts on oil and natural gas for those agents signing contracts in the LNG market whose price is linked to long-term energy indexes or natural gas market benchmarks. Some cross-hedging studies on the issue have been done for other commodities but not for the LNG markets. The methodology to apply would be based on the seminal paper of Anderson and Danthine (1981) and its extensions in which an optimal portfolio problem is built and it is optimized with respect to the futures hedging ratios in a set of futures contracts.

A second research paper could continue the analysis carried out in the second chapter of this PhD dissertation by studying the convenience yield in European natural gas markets. In a context of increasingly liberalized and volatile energy markets and with a growing share of renewables in the energy mix, it is of primary importance to study and understand the determinants and empirical properties of convenience yields and risk premiums for natural gas markets in Europe and the implications of them in hedging strategies. Convenience yield in natural gas markets have been studied in US, but not in Europe (see Milonas and Paratsiokas (2017) and Modjtahedi and Movassagh (2005)). The aim of this research would be to uncover the determinants and empirical properties of convenience yields and risk premiums in European markets. Results on European markets would have significant differences to the existing literature in the US market because of the differences in pricing factors and market structures. The convenience yield and its determinants in European energy markets would be defined. Then, these factors will be introduced in an econometric model to test its sensitivity and statistical significance.

The Iberian natural gas began operating in December 2015. It comprises the Portuguese and Spanish gas systems. Even its development is still very premature and low volumes of gas are negotiated through the hub, its special characteristics like neither gas system has significant gas production of their own, makes the study of this hub very interesting. Virtually all natural consumed in Iberia is imported, either via pipeline or via LNG tankers making the Iberian Peninsula one of the main LNG imports into Europe. When trading volumes are sufficiently significant, studies similar to those made in this thesis may be carried out.

Moreover, the analysis in Chapters I could be extended to German and French gas markets as well as Chapter II to the Dutch market, currently the most developed of all European natural gas markets, comparing the results with the ones obtained in this dissertation and applying other methodologies both to analyze hedging strategies and risk premiums.

References

Anderson, R.W., and Danthine, J. P. (1981). Cross-Hedging. Journal of Political Economy 89, 1182-1196.

Milonas, N., and Paratsiokas, N. (2017). Convenience Yields in Electricity Prices: Evidence from the Natural Gas Market. The Journal of Futures Markets 37, 522–538.

Modjtahedi B., and Movassagh, H. (2005b) Natural-gas futures: Bias, predictive performance and the theory of storage. Energy Economics 27, 617-37.

Resumen

1. Introducción

Dado que ninguno de los tres capítulos que forman parte de esta tesis están escritos en alguna de las dos lenguas oficiales de la Universitat de València, en cumplimiento de su normativa, a continuación, se resume en castellano los capítulos que forman dicha tesis doctoral, describiendo el objetivo de la tesis, la metodología empleada, los principales resultados obtenidos y las conclusiones que se derivan de ellos.

La presente tesis ha cubierto diferentes aspectos de los mercados europeos del gas natural y la electricidad, en particular algunas propiedades que afectan a la efectividad de la cobertura, como la estacionalidad en varianza y en precios. Asimismo, se ha realizado un estudio de la prima de riesgo del gas natural, su relación con las variables de riesgo y su descomposición en una prima de riesgo de reinversión o 'rollover' y una prima de 'preferencia por liquidez' relacionada con el plazo. La tesis se compone de tres capítulos: el Capítulo I estudia la estacionalidad en los precios y la volatilidad y cómo mejora la efectividad de la cobertura teniendo en cuenta dicha estacionalidad; el Capítulo II analiza la prima de riesgo convencional y de rollover y su diferencia y cómo se relacionan con factores de riesgo específicos a lo largo del tiempo; y el Capítulo III evalúa la efectividad de la cobertura del 'spark spread' usando conjuntamente los precios de futuros de electricidad y gas natural.

La progresiva liberalización de los mercados de gas europeos ha creado la necesidad por parte de los operantes en el mismo de instrumentos para la gestión del riesgo de precio. En un contexto de fuerte incremento de los precios y de la volatilidad en los mercados energéticos resulta de gran utilidad diseñar estrategias de cobertura del riesgo de precio de dichos activos. En los mercados de gas natural, al igual que otros mercados energéticos, los cambios en el precio de contado son parcialmente predecibles debido a la influencia en ellos de la climatología y la fuerte demanda estacional.

La Unión Europea comenzó el proceso de liberalización de los mercados de gas natural en los años noventa. El objetivo era lograr un mercado más competitivo y la unificación e integración de los diferentes mercados nacionales. El proceso se inició con la promulgación de la Primera Directiva del Gas (98/30/CE) a la que siguieron la Segunda Directiva del Gas (2003/55/CE) y la Tercera Directiva del Gas (2009/73/CE). Medidas como la separación legal de los negocios de los proveedores de energía y de los operadores de redes y la introducción del acceso libre tanto al mercado mayorista como al mercado minorista establecieron el camino para aumentar la competencia. Cada mercado analizado en esta tesis, ha seguido un camino diferente y con distintos grados de cumplimiento hacia un mercado más competitivo y abierto. El primer mercado europeo de gas natural en comenzar el proceso de liberalización fue el británico, después de la promulgación de la "Gas Act" en 1995.

El consumo de gas natural creció rápidamente en la Unión Europea desde la década de 1960, especialmente después del descubrimiento de gas natural en Groningen y el Mar del Norte, alcanzando una posición dominante en la generación de electricidad en algunos países. En los últimos años, esta tendencia ha cambiado desde la irrupción de las energías renovables. El gas natural es la principal fuente de energía en el mix energético en Reino Unido y Holanda.

2. Objetivos y metodología

Los objetivos principales de esta tesis doctoral son el análisis y gestión del riesgo de precio con contratos a plazo sobre el gas y el estudio de la formación de precios a plazo en el mercado de gas europeo y su descomposición entre precio esperado y primas de riesgo. En concreto se han diseñado y estudiado estrategias de cobertura del riesgo de precio del gas natural en Europa con contratos a plazo, así como estrategias de cobertura del contrato spark spread. También se ha caracterizado el comportamiento de la prima de riesgo y su relación con variables de riesgo y/o de poder de mercado, descomponiendo los precios a plazo en precio esperado y prima de riesgo.

Un rasgo común de los precios del gas natural es que los cambios en el precio spot son parcialmente predecibles debido a la estacionalidad del clima, la demanda y los niveles de almacenamiento. Además de esto, la volatilidad de los precios del gas natural es estacional. En invierno, la gestión activa de los almacenamientos es menos flexible y atenuar los aumentos repentinos de precios es más difíciles que en verano. Asimismo, los costes marginales de producción son mayores, la demanda es más inelástica y las perturbaciones del clima invernal disparan los precios produciendo una volatilidad mayor que en verano.

Existen varias cuestiones en la literatura sobre gestión de riegos en los mercados energéticos que se van a intentar abordar para el caso especial de los mercados europeos de gas natural. Nos centramos en la existencia de patrones estacionales en los primeros y segundos momentos de los rendimientos de los precios y las implicaciones para las coberturas con futuros. En un contexto similar, Chang et al. (2010) encontraron que la efectividad de la cobertura con futuros puede cambiar dependiendo de la tendencia del mercado (alcista/bajista) en los mercados de energía (petróleo y gasolina). La influencia de la estacionalidad en los precios de la energía con fines de cobertura también se ha estudiado en Suenaga et al. (2010). En su opinión, las coberturas estacionales son bastante discrecionales bajo una fuerte estacionalidad en los precios. Tomar posiciones largas distintas en el precio al contado en invierno y verano no tendrían sentido y es mejor no tomar estas posiciones. Sin embargo, en nuestra opinión, las medidas de riesgo sí deben tener en cuenta dicha estacionalidad presente en los precios y volatilidad del gas natural. Esta estacionalidad se va a estudiar en el marco del enfoque de Ederington y Salas (2008).

En Ederington y Salas (2008) se adapta el enfoque del ratio de cobertura de mínima varianza estándar (Ederington, 1979) al caso en que los cambios en los precios spot son parcialmente predecibles. En este contexto, muestran que el riesgo de la posición al contado está sobreestimado, la reducción del riesgo alcanzable subestimada, y se obtienen estimaciones más eficientes en los ratios de cobertura. Ederington y Salas (2008) proponen usar la base (precio del futuro menos el precio spot) al comienzo de la cobertura como variable de información para aproximar el cambio en el precio spot esperado. Si los precios de los futuros son predictores insesgados de los precios spot futuros, la base será una medida del cambio esperado en el precio spot hasta el vencimiento (Fama y French, 1987). Este nuevo enfoque se aplica a los mercados europeos del gas por primera vez, tanto al cálculo de los ratios de cobertura como en la medida de la efectividad de la cobertura.

El ratio de cobertura de mínima varianza se define como la covarianza entre los rendimientos del precio al contado y los rendimientos del precio futuro dividido por la varianza de los rendimientos del precio futuro. Cuando se asume una distribución de probabilidad incondicional y se considera una relación lineal entre los rendimientos del precio al contado y los del precio a plazo, el ratio de cobertura de mínima varianza se puede estimar mediante mínimos cuadrados ordinarios (MCO) añadiendo una constante y ruido blanco. En este caso, el ratio de cobertura de mínima varianza será el estimador de los rendimientos futuros. Ederington y Salas (2008) proponen usar la base (precio del futuro menos el precio al contado) al comienzo de la cobertura como la variable de información para aproximar el cambio en el precio spot esperado, de esta forma la estimación por MCO del ratio de cobertura de mínima varianza es más eficiente y con menor sesgo.

Otro de los objetivos es comparar la efectividad de la cobertura de las estimaciones incondicionales del ratio de cobertura de mínima varianza mediante regresiones lineales por mínimos cuadrados ordinarios con las estimaciones condicionales de los modelos de volatilidad GARCH multivariantes. Para obtener estimaciones condicionales de los segundos momentos, se sigue un procedimiento de estimación en dos pasos. En primer lugar, se estima un modelo en media y luego los residuos de este modelo se toman como input en el segundo paso para modelizar la varianza condicional. En Efimova y Serletis (2014) la estacionalidad de los precios se recoge con la introducción de los niveles de almacenamiento y temperatura en la ecuación de la media. Como la base contiene toda esta información, sus valores pasados son considerados en el modelo. En concreto se estiman el modelo BEKK de covarianza condicional de Engle and Kroner (1995), un modelo bivariante de covarianza estacional con funciones estacionales y un modelo de covarianza base-estacional en el que la estacionalidad se introduce mediante funciones sinusoidales previamente estimadas para la base.

La reducción del riesgo se calcula comparando la varianza de la estrategia cubierta (varianza de la cartera cubierta) con la varianza de la posición spot no cubierta. La muestra se divide en dos, y se computan las reducciones de riesgo para los períodos *ex ante* y *ex post*. En el período *ex ante* el modelo se reestima cada vez que se considera un nuevo dato. Las estrategias de cobertura se aplican para una semana, un mes, tres y seis meses para los mercados europeos más avanzados, el mercado inglés (NBP-British Nacional Balancing Point), el holandés (TTF-Title Tranfer Facility) y belga (Zeebrugge-ZEE).

En el segundo capítulo de la tesis se realiza un estudio de la prima de riesgo del mercado británico. La prima de riesgo puede verse como el rendimiento esperado de mantener hasta la entrega una posición en un contrato de futuros. Para estrategias a largo plazo, se pueden tomar posiciones en futuros con vencimiento a largo plazo; o alternativamente, en futuros con vencimiento a corto plazo renovando la posición hasta alcanzar el horizonte deseado. Antes de tomar una decisión, el gestor de la cartera tiene en cuenta los costes de transacción de cada alternativa y los *trade-offs* existentes entre el uso de futuros con vencimiento a largo plazo que se ajustan exactamente al horizonte de planificación deseado y la mayor liquidez de los futuros con vencimiento más cortos. En este segundo ensayo se sigue el artículo de Szymanowska et al. (2014) en el que las primas de riesgo convencionales se descomponen en dos partes: el "componente spot" y el "componente a plazo". En nuestro estudio, el componente spot se denomina prima de riesgo de *rollover* y el término de "componente a plazo" se obtiene como la diferencia entre las primas de riesgo convencionales y de *rollover*. En su trabajo, Szymanowska et al. (2014) argumentan que la prima de riesgo convencional a largo plazo y las primas de riesgo acumuladas a corto plazo difieren ya que cada una está relacionada con diferentes factores de riesgo. Las primas de riesgo acumuladas a corto plazo estarán estrechamente relacionadas con el riesgo de precio al contado, mientras que las primas a largo plazo reflejan principalmente el riesgo presente en el *convenience yield*. Nuestro objetivo es cuantificar las primas de riesgo para ambas alternativas e intentar explicarlas con factores de riesgos específicos basados en consideraciones de equilibrio. También analizamos la evolución de las primas (la prima de riesgo convencional, la prima de riesgo acumulada y la diferencia de ambas) a lo largo del tiempo. Para ello se estima un modelo de regresión lineal en el que las primas se explican mediante factores de riesgo, como son la desviación estándar del precio medio diario del gas del sistema (*system average Price, SAP*[1]), los cambios en los niveles de reservas de gas natural en el Reino Unido de un mes respecto al anterior y los shocks de demanda inesperados modelizados mediantes las sorpresas en los Heating Degree Days (HDD[2]) en invierno, cuando los niveles de almacenamientos están en mínimos. Y en el caso de la diferencia de primas, además de los anteriores factores, se considera el interés abierto.

Por último, en el capítulo tres se estudia la cobertura del contrato *spark spread* usando contratos a plazo para coberturas semanales y mensuales. El *spark spread* se puede definir como el margen de beneficio bruto obtenido al comprar y quemar gas natural para producir electricidad. El tamaño de esta ganancia depende de los precios de la energía y la eficiencia del generador. El *clean spark spread* minora el *spark spread* con el coste de emitir CO_2 a la atmósfera. La curva forward del *spark spread* es muy importante para los productores de energía, ya que proporciona un método para que éstos aseguren beneficios en la generación de la electricidad. La curva forward del *spark spread* y sus valores promedio pueden indicar a las empresas productoras de electricidad mediante gas cómo maximizar los beneficios en sus operaciones a plazo eligiendo vencimientos con mayores márgenes.

[1] El SAP se calcula como el precio medio ponderado por volumen de todo el gas comercializado a través del mecanismo On-the-day Commodity Market

[2] Los HDD es una aproximación a la demanda de energía necesaria para calentar un hogar o una empresa; se calculan como la diferencia entre la media de la temperatura más alta y más baja de un día y 18 grados centígrados.

El principal objetivo de este tercer capítulo es el estudio de la gestión del riesgo de precio de la electricidad y el gas natural, determinando simultáneamente la posición óptima en futuros sobre electricidad y gas natural para cubrir el riesgo del *spark spread.* Una rasgo común de los precios del gas natural y la electricidad es que los cambios en el precio spot son parcialmente predecibles debido a la estacionalidad del clima, la demanda y los niveles de almacenamiento. Debido a estos efectos estacionales presentes en el *spark spread* sus cambios son parcialmente predecibles. Es por ello que aplicamos al *spark spread* la metodología desarrollada en Ederington y Salas (2008) en la que los cambios esperados en el precio spot se aproximan utilizando la información contenida en la base. Se estudian los siguientes cinco casos tanto para el *spark spread* en horas punta como en horas valle: (i) los ratios de cobertura de la electricidad y el gas se estiman conjuntamente; (ii) los ratios de cobertura de la electricidad y el gas se estiman por separado cada uno en su mercado; (iii) los ratios de cobertura de la electricidad y el gas se estiman conjuntamente pero se restringen a ser iguales; (iv) los ratios de cobertura de la electricidad y el gas se restringen a tomar el valor 1; (v) los ratios de cobertura de la electricidad y el gas toman el valor 0, es decir no hay cobertura.

3. Resultados

En primer lugar, uno de los resultados del primer capítulo es que la base es positiva en invierno y negativa en verano. En invierno, la demanda es grande y los niveles de almacenamiento disminuyen y los costes de almacenamiento aumentan (*convenience yield* positivo), produciendo una base positiva. En verano, la demanda de gas natural es menor debido al clima más cálido y los precios de almacenamiento disminuyen aumentando los niveles de almacenamiento (*convenience yield* negativo). La combinación de estos efectos genera una base negativa. La base y la volatilidad de los rendimientos tienen un patrón estacional similar, son altos en invierno y bajos en verano. Realizando un test de igualdad de medias y varianzas para contrastar que estas diferencias son estadísticamente significativas obtenemos que no se puede rechazar la igualdad de medias estacionales en la base, el spot y los futuros. Por el contrario, la volatilidad en invierno de estas variables es significativamente más alta que la volatilidad en verano. Este componente estacional parece estar presente también en los ratios de cobertura estimados mediante el modelo BEKK y los modelos estacionales, sin embargo no se puede rechazar la igualdad en media con un 5% de significatividad. Respecto a las reducciones de riesgo en el caso de las coberturas semanales, las reducciones de riesgo con el enfoque estándar son subestimadas más de un 10%. Para el mercado británico y belga, el modelo que mejor funciona es el modelo base-estacional, con las mayores reducciones de riesgo, de 46.81% y 44.44% respectivamente. En TTF es la estrategia *naive* la que obtiene la primera posición con un 46.46% de reducción. En los tres mercados, el modelo BEKK es el que consigue peores resultados. En el caso de las coberturas a más largo plazo, a uno, tres y seis meses, la subestimación en la reducción del riesgo que se obtiene con el enfoque estándar varía entre un 40% y más del 100%. Las reducciones de riesgo obtenidas mediante la estrategia *naive* y MCO varían entre el 79% y el 93% para el periodo *ex ante.* Existe claramente un efecto duración positivo en la efectividad de la cobertura. Las reducciones conseguidas son mayores en un mes que en una semana. En el caso de UK se llevan a cabo coberturas a tres y seis meses con los mejores resultados conseguidos para las coberturas a seis meses, aunque las reducciones de riesgo de ZEE y TTF para un mes son casi tan altas como las de seis meses en NBP. Respecto a los ratios de cobertura con base y sin base calculados mediante mínimos cuadrados ordinarios, los ratios de cobertura considerando la base se sitúan por encima de los ratios de cobertura sin tener en cuenta la base, en los tres mercados. El resultado contrario sucede para NBP con los períodos de cobertura más largos. A pesar de que con el enfoque Ederington y Salas (2008) se obtienen estimaciones más eficientes del ratio de cobertura, eso no implica una mejora en la efectividad de la cobertura. Finalmente, los ratios de cobertura estimados mediante modelos GARCH obtienen peores reducciones del riesgo comparados con los ratios obtenidos mediante mínimos cuadrados ordinarios, incluso la estrategia *naive* es mejor en el caso de coberturas semanales para TTF. Con el fin de probar que las reducciones de riesgo de varianza son estadísticamente significativas, se realizó el test de White (*reality check)* para cada par de estrategias de cobertura concluyendo que las diferencias en la efectividad de la cobertura son estadísticamente significativas en todos los casos.

En cuanto al análisis de la prima de riesgo realizado en el segundo capítulo se obtienen varios resultados interesantes. En primer lugar, todos los valores promedio de las primas de riesgo para todo el período son significativamente diferentes a cero, positivos y aumentan con el vencimiento. La prima de riesgo a una día toma valores entre 0.41 peniques ó 0.5 por ciento, en rendimientos logarítimicos o realizados. Esto significa que vendiendo simultáneamente gas natural a un día y comprándolo al día siguiente en el mercado spot, reportará un beneficio de 0.5% del valor total de la cartera cada día, o equivalente, alrededor de 180% de rendimiento al año si esta estrategia se repite todos los días. Las primas de riesgo convencionales varían entre 0,99 y 6,14 peniques o entre 4,32 y 15,64 por ciento para los contratos entre uno y seis meses hasta la entrega. Finalmente, las primas de *rollover* son significativamente más altas, entre 0,24 y 3,52 peniques; o entre 1.26 y 10.54 por ciento para vencimientos entre tres y seis meses, tanto para invierno como para verano. Se puede concluir que la prima de riesgo acumulada en las estrategias de *rollover* es significativamente mayor que las primas de riesgo convencionales, y además aumenta con el tiempo hasta la entrega. Por ejemplo, terminar una estrategia de negociación con futuros cuyo vencimiento es enero con posiciones contratadas seis meses antes, implicaría una prima de riesgo media a la entrega de 23.96 por ciento para una sola transacción y de 33.56 por cierto encadenando posiciones. Los meses de invierno contienen las primas de riesgo más altas y más volátiles, tanto para la prima de riesgo convencional como para la prima de *rollover*, concretamente los meses de enero y febrero. Finalmente, se analiza la evolución temporal de la prima de riesgo en un modelo de equilibrio, utilizando un modelo de regresión lineal con factores de riesgo que afectan a los posibles participantes. La volatilidad del precio spot es siempre significativa, consecuentemente las primas de riesgo están íntimamente relacionadas con la incertidumbre medida mediante la desviación estándar del *SAP*, las primas de riesgo son muy sensibles a los riesgos del mercado spot. Asimismo las primas de riesgo tienen una sensibilidad positiva y significativa a los shocks de demanda inesperados en condiciones de oferta ajustadas. Por último, la respuesta a la variable proxy para los shocks inesperados en los niveles de almacenamiento es negativa en todos los casos, y estadísticamente significativa en la mayoría. También se ha visto que las diferencias entre las primas de riesgo convenional y las de *rollover* pueden explicarse parcialmente por argumentos de liquidez en el mercado de futuros. Se ha introducido el interés abierto cómo variable explicativa de esas diferencias obteniéndose valores negativos y estadísticamente significativos en casi todos los casos. Esto es, una mayor liquidez en el contrato de futuros utilizado para calcular la prima de riesgo convencional reduce las diferencias entre ambas primas de riesgo. Por lo tanto, como la estrategia de *rollover* es la más líquida y contiene la compensación al riesgo más alta, este resultado refuerza la idea de que los agentes prefieren negociar con los contratos más líquidos y están dispuestos a pagar más por ellos.

Por último, en el capítulo tres se estudia el *spark spread* y su cobertura. El primer resultado a destacar es que el *spark spread* y el *clean spark spread* son variables indistinguibles desde el punto de vista de la medición del riesgo ya que ambas variables presentan la misma volatilidad. Además los rendimientos del *spark spread* pueden ser explicados por los valores pasados de sus bases, excepto en el caso del *spark spread* punta para Reino Unido. Esto se explica por la existencia de patrones estacionales en la demanda de productos energéticos, debido a las oscilaciones climáticas a lo largo del año. Consecuentemente, la consideración de la base, que recoge esos patrones estacionales, en la aproximación de Ederington y Salas (2008) mejora notablemente los resultados respecto al enfoque estándar. Todos los ratios de cobertura, excepto en el caso del gas natural, son positivos y los resultados para la electricidad son similares a los del *spark spread*. Además, las coberturas mensuales obtienen una mejor efectividad de la cobertura que las coberturas semanales, como sucedía en el capítulo uno con las coberturas de los precios de gas natural. Si nos fijamos en los cinco casos analizados, no existe una estrategia de cobertura que claramente domine las estrategias restantes, depende del período analizado, de la frecuencia de la cobertura, de si consideremos horas puntas o horas valle o del mercado en cuestión. Para Alemania y los Países

Bajos los resultados son mucho mejores que para el Reino Unido en los que se obtienen las peores reducciones del riesgo del *spark spread* en todos los casos considerados. Asimismo, las mejores estrategias de cobertura mensual pueden lograr reducciones de riesgo que oscilan entre 20.05 y 48.90. Por último, cuando se consideran las coberturas individuales del mercado eléctrico (tanto horas punta como horas valle) y el mercado gasístico con sus respectivos futuros, los resultados mejoran considerablemente respecto a la cobertura conjunta del *spark spread*, sobre todo en el caso del gas natural que es el activo más fácil de cubrir[3], llegando a alcanzar un 56.44 por ciento para coberturas mensuales.

4. Conclusiones

En el capítulo uno se ha aplicado el enfoque de Ederington y Salas (2008) para los mercados de gas natural europeos, en concreto al mercado de gas de Reino Unido, de Bélgica y de Holanda. En el cálculo de los ratios de cobertura de mínima varianza, se han obtenido mejoras significativas en la efectividad de la cobertura de las estrategias consideradas en la gestión del riesgo de precio cuando se considera el cambio esperado en los precios al contado. Las características estadísticas especiales de los precios del gas natural pueden producir reducciones de riesgo incorrectas que pueden corregirse utilizando este nuevo marco. La efectividad de la cobertura también se puede mejorar significativamente al aumentar la duración de la cobertura. Dependiendo de la duración de la cobertura (una semana, o uno, tres y seis meses), y el subperíodo analizado (subperíodos dentro de la muestra y fuera de la muestra) la reducción del riesgo alcanza valores de entre 44% y 93%. También se ha encontrado una fuerte estacionalidad en la volatilidad de los rendimientos de los precios spot y futuros, son significativamente más altos en invierno que en verano. Esta estacionalidad detectada se ha considerado en las estimaciones de las estrategias de cobertura estudiadas, consiguiéndose mejoras notables en los resultados. Por último, resaltar que las estrategias de cobertura de los modelos estacionales, las estrategias basadas en regresiones lineales

[3] Liu et al. (2017) obtienen la misma conclusión para el *crack spread* y sus componentes individuales.

o incluso una estrategia *naive*, obtienen mejores resultados que los métodos estadísticos más sofisticados tipo *BEKK*. En consecuencia, no parece que modelos estadísticos más avanzados y con mayor complejidad en la estimación garanticen una mejor efectividad de la cobertura.

En el segundo capítulo de la tesis los resultados obtenidos coinciden con los de Szymanowska et al. (2014) ya que las primas de riesgo en los futuros de gas natural del Reino Unido están dominadas por el 'componente spot' (las primas de riesgo de *rollover* exceden las primas de riesgo convencionales). También se han detectado patrones estacionales en media y volatilidad en las primas de riesgo de *rollover*, en las primas de riesgo convencionales y en la diferencia entre ellos. Los meses de invierno presentan primas de riesgo más altas y volátiles. En cuanto al análisis de los factores de riesgo específicos de este mercado basados en modelos de equilibrio teórico, los resultados muestran que los factores de riesgo analizados (volatilidad de los rendimientos del precio spot, shocks inesperados de demanda bajo condiciones de suministro ajustadas y shocks inesperados en los niveles de almacenamientos) pueden explicar las primas de riesgo realizadas variables en el tiempo de forma similar a la predicha por la teoría. Se concluye que una parte importante de las primas de riesgo esperadas se valora según consideraciones de riesgo. Finalmente, la liquidez en los mercados de futuros parece ser la variable más importante en el análisis de la diferencia entre las primas de riesgo convencionales y de *rollover*. Este resultado implica que los argumentos de liquidez son importantes en la determinación de los precios de los futuros y la preferencia por la liquidez se paga cuando se adopta una estrategia de *rollover*.

Por último, en el tercer ensayo de esta tesis doctoral, se ha analizado la cobertura del contrato *spark spread* con futuros. Al comparar el riesgo del *spark spread* y del *clean spark spread* se observa que ambas variables son indistinguibles y la dimensionalidad del problema se puede reducir considerando solo los precios de la electricidad y el gas natural sin tener en cuenta el CO_2. Esto se debe a que los precios spot y de futuro del CO_2 están casi perfectamente correlacionados y el riesgo de base para una cobertura es el mismo en ambos *spreads*. En el tercer capítulo también se aplica el enfoque de Ederington y Salas (2008) porque los rendimientos del *spark spread* pueden anticiparse parcialmente debido a la existencia de un claro patrón estacional en él, consiguiéndose mejoras en la efectividad de la cobertura respecto al enfoque de mínima varianza clásico, ya que la reducción del riesgo se infraestima con éste último. Otro resultado a resaltar es que la gestión individualizada del riesgo de los precios de la electricidad y el gas natural no siempre es la mejor solución. Cubrir el *spark spread* con futuros es más difícil que cubrir los riesgos de precio de la electricidad y el gas natural con sus respectivos contratos de futuros. Mientras que la reducción del riesgo del *spark spread* para períodos mensuales alcanza valores de entre 20.05 y 48.90 por ciento, para el riesgo de precio de la electricidad las reducciones oscilan entre 48.69 y 69.06 por ciento para precios en las horas valle, y entre 31.22 y 55.89 por ciento para precios en las horas punta. En el caso de los precios del gas natural, las estrategias óptimas para períodos mensuales producen reducciones de riesgo que oscilan entre el 56.54 y el 61.77 por ciento.

Bibliografía

Chang, C. Y., Lai, J. Y., and Chuang, I. Y. (2010). Futures Hedging Effectiveness under segmentation of bear/bull energy markets. Energy Economics 32, 442-449.

Ederington, L. H., & Salas, J. M. (2008). Minimum variance hedging when spot price changes are partially predictable. Journal of Banking and Finance, 32, 654-663.

Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. Econometric Theory, 11, 122-50.

Fama, E. F., and French, K. R. (1987). Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage. Journal of Business, 60, 55-74.

Liu, P., Vedenov, D., and Power G.J. (2017). Is hedging the crack spread no longer all it's cracked up to be? Energy Economics 63, 31-40.

Suenaga, H., Smith, A., and Williams J. (2008) Volatility dynamics of NYMEX natural gas futures prices. The Journal of Futures Markets 28, 438-463.

Szymanowska, M., De Roon, F., Nijman, T., and Van den Goorbergh, R. (2014) An Anatomy of Commodity Futures Risk Premia. The Journal of Finance 69, 453-482.